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Optimizing Aircraft Availability: Where to Spend Your Next O&M Dollar

Frederick G. Fry

OPTIMIZING AIRCRAFT AVAILABILITY:

WHERE TO SPEND YOUR NEXT O&M DOLLAR

THESIS

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AFIT/GCA/ENV/10-M03

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Abstract

In the current fiscally constrained environment, the Air Force must allocate resources where they are most needed and will be most effectively used. For aircraft, this means spending money on weapon systems in a manner that optimizes aircraft availability rates, thereby maximizing the warfighting capability of the Air Force. With that in mind, this thesis endeavors to improve the analytical capability of the Air Force by demonstrating a definitive link between operations and maintenance (O&M) spending and aircraft availability rates. In order to do that, explanatory regression models are developed that show the relationship between O&M spending and AA rates, while controlling for as many other significant variables as the data allow. Ultimately, this research was unable to show that aircraft availability rates are significantly influenced by changes in O&M spending; however, suggestions for future research and potential policy implications are discussed.

AFIT/GCA/ENV/10-M03

This work is dedicated to my wife and son. Their tremendous love, support, and understanding during the past 18 months made it possible for me to make the most of my experience at AFIT.

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Rick Fry

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I: Introduction

Background

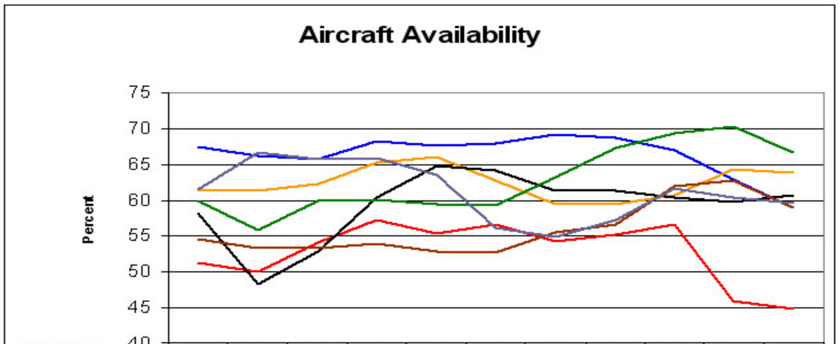
In his leadership message, the Assistant Secretary of the Air Force for Financial Management and Comptroller, Dr. Jamie M. Morin stated,

> *in this time of scarce resources … every dollar wasted or inefficiently expended is an additional debt passed on to our children. … we are all charged with balancing the imperative of effectively using resources to accomplish vital national goals with the need to continuously … provide the capabilities needed in the wars we are fighting today, and prepare for the uncertain conflicts of the future* (2009).

Regardless of the dollar value of the bottom line Air Force budget, Air Force decision makers should expend resources in the most effective manner possible. That is, use resources where they will have the most positive effect on the mission.

The mission of the United States Air Force is to "fly fight and win … in air, space and cyberspace" (Donley and Schwartz, 2009:3). While the Air Force employs many assets to achieve this mission, the most obvious and direct tools used are aircraft. Whether the mission is close air support, airlift, aerial refueling, or reconnaissance, the availability of necessary aircraft to perform the mission is a vital concern. Accordingly, the Air Force spends a significant portion of its budget each year to sustain its aircraft. In fiscal year (FY) 2009, the Air Force spent $42.1 billion on operations and maintenance (O&M) to support its people and equipment. Of those O&M expenditures, the money spent directly on flying operations totaled $14.7 billion, which amounts to 12.9% of the baseline budget (SAF/FMB, 2009).

Although the Air Force allocates a nontrivial portion of its budget to support its aircraft, aircraft availability (AA) rates rise and fall with regularity. Figure 1 shows the availability rates of aircraft by mission type from FY1999 to FY2009. As we can plainly see, AA rates fluctuate drastically for each of the weapon system types shown from year to year. Although it would be helpful to compare the historical AA rates to the goals set for each weapon system over the same period, the Air Force did not begin establishing AA standards until 2008. Prior to that, the Air Force focused most of its attention on mission capable (MC) rates and the major commands (MAJCOMs) were primarily responsible for setting their own goals (Tyler, 2009).



Fiscal Year	FY99	FY00	FY01	FY02	FY03	FY04	FY05	FY06	FY07	FY08	FY09
Fighters	67.5	66.2	65.7	68.3	67.7	67.9	69.2	68.7	67.1	62.8	58.9
Bombers	51.2	50.1	54.1	57.2	55.3	56.5	54.3	55.1	56.6	45.9	44.8
Airlift	61.3	61.3	62.2	65.2	66.0	62.7	59.4	59.4	60.7	64.3	63.9
KC-135	58.2	48.2	52.7	60.5	64.8	64.2	61.4	61.3	60.4	59.7	60.8
ISR	60.0	55.7	59.8	60.1	59.4	59.3	63.1	67.3	69.3	70.3	66.8
CSAR	54.5	53.4	53.3	54.0	52.7	52.6	55.4	56.6	62.0	62.7	59.0
SOF	61.5	66.8	65.7	65.9	63.6	56.0	54.9	57.2	61.6	60.5	59.5

Figure 1: Aircraft Availability Rates, FY99 - FY09 (Tirpak, 2009)

With that said, Air Force leaders should have a better understanding of the factors that influence AA rates so that they are able to affect positive change. Without an adequate number or the right combination of available aircraft, the Air Force may not be able to accomplish its mission. In our study, we build on previous research to gain a better understanding of the factors that affect AA rates. Specifically, we show the affect that O&M costs have on AA rates, which will allow Air Force leaders to use O&M resources as a means to control the AA rates of the Air Force fleet.

Purpose of This Study

In this study, we seek to determine which factors significantly affect aircraft availability rates; O&M costs will be our primary independent variable of interest. In order to do that, we develop explanatory multiple regression models that show relationships between O&M costs and AA rates, while controlling for as many other significant variables as our data allow. We use these findings to improve the analytical capability of the Air Force when trying to determine how to allocate resources so that O&M funding may be used as a tool to optimize aircraft availability.

Research Objective

The objective of this research is to develop explanatory models that demonstrate a definitive link between O&M costs and aircraft availability.

Research Questions.

1. What variables are significant predictors of aircraft availability rates?

2. Are aircraft availability rates influenced by changes in O&M spending?

3. Do the aircraft availability rates of some weapon systems respond to changes in O&M costs more than others?

4. Can a single model be developed to represent multiple Mission Design Series (MDS)?

5. Can the models produced by this research be used as an effective decision tool for the Centralized Asset Management (CAM) office?

Chapter Summary

In this chapter, we described the current fiscal environment in which the Air Force must operate. We outlined the need for a robust analytical process or tool that can guide resource allocation decisions in an attempt to optimize aircraft availability. Finally, we outlined the purpose of this study and listed our research questions.

The rest of this paper is structured as follows: Chapter II provides background relating to aircraft availability, a summary of previous research, and a review of the resource allocation process. In Chapter III, we describe our dataset and outline the methods that will be used to analyze our data. Next, we present the results and analysis in Chapter IV. Finally, we summarize the results and provide policy implications based on our findings in Chapter V.

II: Literature Review

Given our research questions and overall objective, we seek to expand our knowledge concerning aircraft availability and the variables that may affect AA rates. We begin this chapter by discussing the importance of maintaining an adequate quantity of mission capable aircraft and provide an overview of the metrics used by the Air Force to assess the health of its fleet. Next, we summarize the findings of previous research concerning the factors that may affect aircraft availability. Then, we review several models that have been developed and used by the Air Force to forecast aircraft availability. Finally, we provide the reader with an understanding of both the old resource allocation process and the new process developed through ongoing Air Force initiatives.

Mission Impact of Low Aircraft Availability Rates

As we stated earlier, the mission of the U.S. Air Force is "to fly, fight and win … in air, space and cyberspace." To achieve that mission, the Air Force relies on its six "distinctive capabilities" which include the following (DAF, 2003):

1. Air and Space Superiority
2. Global Attack
3. Rapid Global Mobility
4. Precision Engagement
5. Information Superiority
6. Agile Combat Support

Not surprisingly, each of these capabilities depends entirely or in part on the availability of the right mix of Air Force aircraft. Simply put, without a sufficient number of mission capable aircraft ready to fly at any given time, the Air Force cannot perform its stated mission.

The importance of AA extends to the unit-level as well. Perhaps the most direct costs associated with inadequate AA are lost training opportunities. Pilots and their associated aircrew members require a certain number of sorties and flying hours per month depending on the aircraft they fly and the missions they are training to support. AFI 11-(MDS specific volume) specifies exactly what is required for each weapon system aircrew to maintain combat mission ready (CMR) status (Lipina, 2009). AFI 11-2F-16 Volume 1 defines CMR as "the minimum training required for pilots to be qualified and proficient in all of the primary missions tasked to their assigned unit and weapon system" (DAF, 2007:8). In the case of F-16 aircrew, pilots are required to fly nine or ten sorties per month depending on whether they are experienced or inexperienced. If this training requirement cannot be met because not enough aircraft are available, aircrew members may be placed on probation or non-CMR status at the discretion of the squadron commander. If aircrew members who are on probation fail to meet the minimum CMR requirements the following month, they will be demoted to non-CMR status (Lipina, 2009). This scenario would result in degraded readiness of an entire unit and decreased operational flexibility.

Maintainers experience lost training opportunities as well. When AA rates are low, maintainers feel pressure to fix aircraft quickly using whatever resources are available. Often this means cannibalizing parts from one aircraft to support another aircraft. Cannibalizing parts requires a maintainer to spend time removing a part from one aircraft and then installing the part on another aircraft. The extra time involved may result in lost training opportunities for themselves or a lost opportunity to train others (Oliver, 2001).

Many of the other costs associated with low AA rates are so intertwined with AA rates themselves that it is hard to decouple the cause and the effect. For example, low AA rates decrease morale and increase the workload and stress for maintainers, which may negatively affect retention rates. When second term and career airmen decide to separate, the workload increases for the remaining airmen, especially the 5- and 7-level maintainers. Not only do these technicians have to perform more work on aircraft, but also their supervisory and training responsibilities increase as the ratio of 3-level airmen increases. This means that the need for supervision and on-the-job training increases at the same time the workload increases because of the need to generate aircraft (Oliver, 2001). As we have shown here, the cost of low AA rates are extensive and may have enduring negative consequences.

Fleet Management Metrics Overview

In Air Force maintenance organizations, metrics are used extensively to assess the quality, quantity, and timeliness of the maintenance actions being performed as well as the overall health of the fleet and even the readiness of the personnel. However, when it comes to measuring the health of the fleet and the effectiveness of the maintenance performed, the two metrics that dominate are the AA rate and the MC rate.

According to Air Force Instruction 21-101 (AFI 21-101) *Aircraft and Equipment Maintenance Management*, the MC rate is the percentage of unit-possessed hours that aircraft are either fully mission capable (FMC) or partially mission capable (PMC) for a specific period of measurement (e.g., weekly or monthly). FMC status simply means that an aircraft can perform all of its assigned missions. PMC status means that an aircraft can perform at least one, but not all of its assigned missions (DAF, 2006). MC rate is calculated using equation 1.

$$MC\ Rate\ (\%) = \frac{FMC\ Hours + PMC\ Hours}{Unit\ Possessed\ Hours} \times 100 \tag{1}$$

AA, as defined by AFI 21-101, is the percentage of a fleet not in a depot status or not mission capable (NMC) status. Alternatively, the AA rate is the percentage of a fleet's total active inventory (TAI) that is available (mission capable). NMC aircraft are aircraft that are unable to perform any of their wartime missions (DAF, 2006). The AA rate is calculated using equation 2.

$$AA\ Rate\ (\%) = \frac{MC\ Hours}{TAI\ Hours} \times 100 \tag{2}$$

Intuitively, the complement of availability is nonavailability, which consists of five components: the unit possessed not reported (UPNR) rate, the depot rate, the not mission capable maintenance (NMCM) rate, the not mission capable supply (NMCS) rate, and the not mission capable both (NMCB) rate (AFLMA, 2009). Insight into why AA rates are low may be garnered from investigating these five areas of nonavailability, which we will briefly explain.

As the name states, the UPNR rate is the percentage of a fleet's TAI that are unit possessed, but not reported. When an aircraft suffers major damage or is in need of major maintenance, the owning unit may be required to wait for higher headquarters to make a decision regarding how to proceed. During this time, the aircraft would be UPNR because the unit is waiting to be told what to do next. Not surprisingly, the depot rate is the percentage of a fleet's TAI that are in depot status. Typically, these aircraft are either awaiting or undergoing depot level maintenance (AFLMA, 2009). The NMCM rate is the percentage of possessed aircraft that are unable to perform primary assigned missions because the aircraft is in need of maintenance that will be carried out by the unit. The NMCS rate is the percentage of possessed aircraft that are unable to execute primary missions for supply reasons (e.g., lack of spare parts). Finally, the NMCB rate is the percentage of possessed aircraft that are unable to perform primary assigned missions for both maintenance and supply reasons (DAF, 2006).

As stated in the Air Force Logistics Management Agency's handbook titled *Maintenance Metrics U.S. Air Force* and consistent with the goals of Expeditionary Logistics for the 21st Century (eLog21), the AA rate is the metric that will be used to measure the health of the fleet (AFLMA, 2009). The primary reason that the AA rate is a more useful metric than the MC rate is that it reflects a more complete picture of the fleet. While the numerator is the same for both metrics, the denominator is different which results in a gap between the two rates. The MC rate only considers aircraft that are possessed by operational units and ignores aircraft that are in UPNR and depot status. This means that the denominator is a fluid number and will always result in a rate that is greater than the AA rate. The AA rate on the other hand reflects all aircraft in the fleet. Simply put, the AA rate answers a question that is central to assessing combat capability: How many jets are ready to fly?

Previous Research Reveals Factors Affecting Aircraft Availability

In our review of literature from the 1990s to 2009, we found an abundance of research completed by the Air Force Institute of Technology (AFIT), the Naval Postgraduate School (NPS), RAND, the Government Accountability Office (GAO), and the Air Force Logistics Management Agency (AFLMA). The majority of these studies focused on identifying predictive factors to be used in forecasting MC rates. While these studies have contributed a significant amount to the existing knowledge on AA, none of the research has focused directly on O&M costs. Our investigation seeks to close this gap in knowledge.

Although our research focuses on AA, the majority of prior research discusses MC rates. The reason for this is that MC rates were the most commonly used metric to assess fleet health until 2004 when Air Force decision makers introduced the AA metric as a part of eLog21 to provide an enterprise view of the total fleet (Tyler, 2009). Since that time, some research has focused on AA rates and the factors that go into it, but not enough for the purposes of our literature review. Nevertheless, research regarding MC rates will be sufficient since we know that total MC hours are the most significant factor in determining AA rates.

A study published in *Air Force Journal of Logistics* in 2001 identified 53 variables that may affect MC rates (Table 1). Previous research and history have shown that these factors may be grouped into six main categories: personnel, environment, reliability and maintainability, funding, aircraft operations, and logistics operations. While it is doubtful that an entirely complete list of factors could be created, this table serves as a very good starting point for our research. We will briefly discuss several of the more prevalent factors below.

Table 1: Potential Factors Affecting MC Rates (Oliver, et al., 2001)

Personnel	Environment	Reliability & Maintainability	Funding	Aircraft Operations	Logistics Operations
Personnel assigned or authorized	OPSTEMPO factors	TNMCM hours	Replenishment spares funding	Aircraft utilization rates	TNMCS hours
Personnel in each skill-level (1, 3, 5, 7, 9 and 0)	PERSTEMPO factors	Maintenance downtime/reliability	Repair funding	Possessed hours	Base repair cycle time
Personnel in each grade (E1-E9)	Number of deployments	Mean time between failures/mean time to repair	General support funding	Average sortie duration	Order and ship time
F-16 maintenance personnel in various Air Force specialty codes (AFSC)	Policy changes	Code 3 breaks	Contractor logistics support funding	Flying hours	Level of serviceable inventory
F-16 maintenance personnel by skill-level per AFSC	Contingencies	8-hour fix rate	Mission support funding	Sorties	Level of unserviceable inventory
F-16 maintenance personnel by grade per AFSC	Vanishing Vendors	Reparable item failures	O&M funding	Flying scheduling effectiveness	Supply reliability
Retention rates for F-16 maintenance personnel	Weather	Cannibalization hours/actions	Initial spares funding	Type mission (DACT, CAP, and so forth)	Supply downtime
Personnel per aircraft ratios	Aircraft age	Repair actions/hours	Acquisition logistics funding	Over-Gs	Depot repair cycle time
Maintenance officers assigned or authorized	Aircraft mission (training, test, combat)	Maintenance man-hours		Airframe hours	Maintenance scheduling effectiveness

Personnel

In his 2001 AFIT thesis, Captain Steve Oliver used correlation and regression analysis to identify factors associated with MC rates of F-16C/D aircraft. His results showed that as the number of inexperienced personnel (measured by rank or skill level) increased, MC rates decreased. Higher ratios of 3-levels to either 5- or 7-levels (or both) were also negatively correlated to MC rates. Concerning reenlistment rates, Oliver determined that first term and career airmen along with the overall reenlistment rate were positively correlated with MC rates. Additionally, the reenlistment rate of eligible crew chiefs showed a high degree of positive correlation. Finally, the ratio of maintainers per aircraft, and total maintainers assigned demonstrated strong positive correlations (Oliver, 2001).

In a 2003 report, the GAO determined that shortages of maintenance personnel as well as a lack of experienced maintainers contributed to low MC rates (GAO, 2003). Similarly, research completed in 2004 on C-17 MC rates showed that crew chief manning levels have a significant positive relationship with MC rates (Huscroft, 2004). Finally, an article published in the Air Force Journal of Logistics in 2007 examined F-16C/D MC rates and found the percentage of 7- and 9-level maintainers to be significant in explaining MC rates. Specifically, the authors developed a model using just these two dependent variables to explain 82 percent of the variance observed in MC rates (Chimka and Nachtmann, 2007).

Environment

Concerning the operational environment, Capt Billy Gilliland used regression to test the relationship between 13 common measures of aircraft maintenance and several dependent variables in his 1990 AFIT thesis. Among other findings, the analysis showed a positive correlation between MC rates and the average number of possessed aircraft (Gilliland, 1990).

Intuitively, aircraft age is a likely consideration when discussing availability. The GAO confirmed this notion citing aircraft age as a factor that affects MC rates. According to interviews with logistics officials from the services, aircraft failure rates follow a curve that is similar to the "bathtub curve" depicted in Figure 2. While the Air Force's inventory continues to age, failures become more common as aircraft reach the end of their useful life. Exacerbating this effect are increased deployments over recent years, which has forced aircraft to operate at higher than normal rates and has accelerated aging concerns (GAO, 2003).

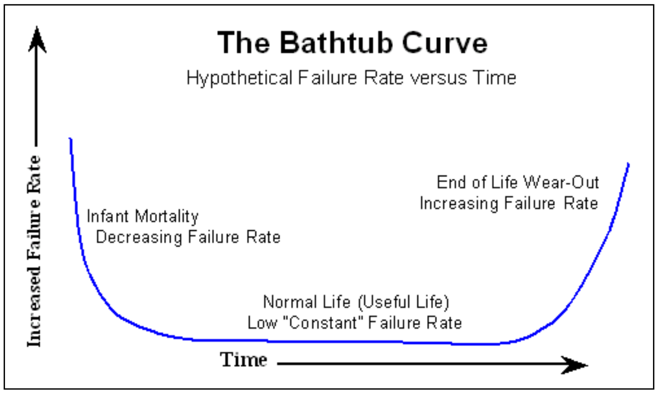


Figure 2: Bathtub Curve (Wilkins, 2002)

Prior to 2002, the Air Force structured its flying units under what was called an "Objective Wing Structure." Maintenance organizations reported to either the operations group commander or the logistics group commander. In October of 2002, the Air Force transitioned to the "Combat Wing Structure," which aligned all maintenance units under a maintenance group commander with the goals of "enhancing core competencies, improving aircraft sortie production, and improving fleet health" (Barthol, 2005:3). Research completed in 2005 concluded that this organizational change was effective in meeting its stated goals (Barthol, 2005).

Reliability & Maintainability

Gilliland showed a negative correlation between MC rates and both the cannibalization rate and awaiting maintenance discrepancies (Gilliland, 1990). Next, Lieutenant Commander Patricia Moore showed that cannibalizations are negatively correlated with FMC rates of deployed aircraft (Moore, 1998). Lastly, Oliver's research found a strong positive correlation linking 8-hour fix rates and MC rates (Oliver, 2001).

Funding

According to a RAND study completed in 2009, aircraft maintained by contractor logistics support (CLS) have a higher proportion of contractually fixed costs each year than organically supported aircraft. RAND states that as a result "CLS programs have been less affected by funding instability than have organically supported programs, which must often reduce funding for spare parts when budgets are cut" (Boito, 2009:46). To illustrate this point, RAND compared the total not mission capable supply (TNMCS) achieved rates and standards between CLS and organically supported aircraft with the same mission over a three-year period. Figure 3 illustrates a representative sample of their findings (Boito, 2009).

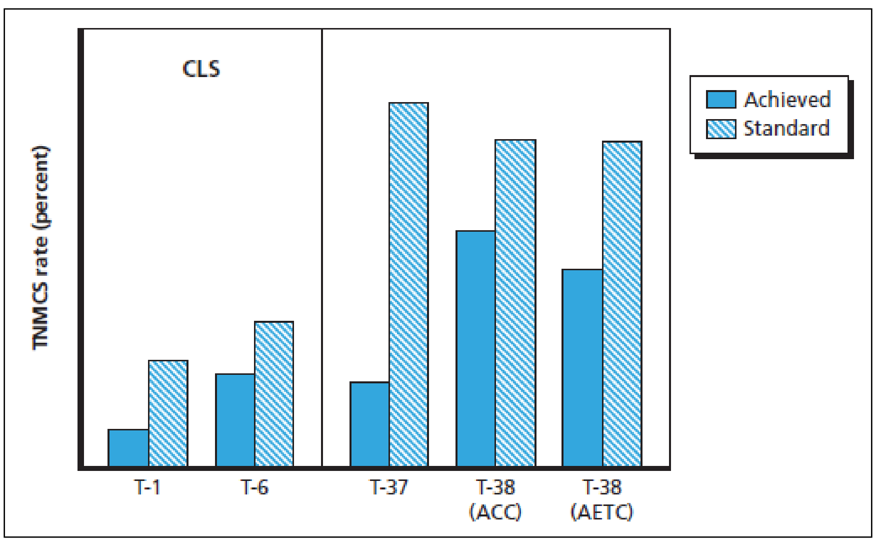


Figure 3: Comparison of TNMCS Rates and Standards for CLS and Organically Supported Trainer Aircraft (Boito, 2009)

While all aircraft exceeded their respective standard, CLS aircraft are held to a much tougher standard than organic aircraft. RAND argues that CLS aircraft achieve better (i.e., lower) TNMCS rates because they receive more funding than organic aircraft.

RAND further concludes that high AA rates are “largely a function of the resources devoted to maintain them” (Boito, 2009:46).

Additionally, the GAO reports that officials from all the services blame underfunding spare parts inventories, maintenance depots, and other areas of maintenance and supply as a reason for low MC rates (GAO, 2003).

Aircraft Operations

Moore’s analysis found that an increase in the number of sorties causes FMC rates to increase; however, an increase in the number of sorties combined with an increase in the number of cannibalizations causes FMC rates to significantly decrease (Moore, 1998).

Logistics Operations

Pertaining to logistics, Gilliland determined that awaiting parts discrepancies are negatively correlated with MC rates (Gilliland, 1990). Moore’s research found that FMC rates increase as the percentage of requests for consumable or repairable items that are filled in one to two days increases (Moore, 1998). Oliver’s research found that the most significant correlations between logistics variables and MC rates appeared with a lag of two quarters; however, the statistical significance was not strong enough to warrant inclusion in his models (Oliver, 2001). Lastly, the GAO reports that shortages of spare parts contribute to low MC rates. They say that this may be caused by underestimates of demand, contracting issues, or other problems (GAO, 2003). We summarize the findings of previous research in Table 2.

Table 2: Variable Correlations with Aircraft Availability Rates

Category	Variable	Correlation	Author
Personnel	Ratio of 3-levels to 5-levels	Negative	Oliver, 2001
	Ratio of 3-levels to 7-levels	Negative	Oliver, 2001
	Total # of Inexperienced Maintainers by Rank or Skill Level	Negative	Oliver, 2001
	Maintainers Per Aircraft	Positive	Oliver, 2001
	Total # of Maintainers	Positive	Oliver, 2001
	Overall Reenlistment Rate	Positive	Oliver, 2001
	Reenlistment Rate of First-Term Airmen	Positive	Oliver, 2001
	Reenlistment Rate of Career Airmen	Positive	Oliver, 2001
	Reenlistment Rate of Eligible Crew Chiefs	Positive	Oliver, 2001
	Crew Chief Manning Levels	Positive	Huscroft, 2004
	Percentage of 7-level Maintainers	Positive	Chimka and Nachtmann, 2007
	Percentage of 9-level Maintainers	Positive	Chimka and Nachtmann, 2007
Environment	Average # of Possessed Aircraft	Positive	Gilliland, 1990
	Aircraft Age	Mixed (Bathtub Curve)	GAO, 2003
	Transition to Combat Wing Structure in 2002	Positive	Barthol, 2005
Reliability & Maintainability	Cannibalization Rate	Negative	Gilliland, 1990; Moore, 1998; Oliver, 2001
	Awaiting Maintenance Discrepancies	Negative	Gilliland, 1990
	8-Hour Fix Rate	Positive	Oliver, 2001
Funding	CLS supported	Positive	RAND, 2009
Aircraft Operations	Sorties	Mixed	Moore, 1998;
Logistics Operations	Awaiting Parts Discrepancies	Negative	Gilliland, 1990
	% of Requests for Consumables Filled in 1-2 days	Positive	Moore, 1998

Establishing Aircraft Availability Goals

According to AFI 21-103, *Equipment Inventory, Status and Utilization Reporting*, "MAJCOMs establish capability goals in coordination with the Air Staff to include but not limited to MC, total not mission capable maintenance (TNMCM), and TNMCS. These goals enable HQ USAF to assess resource allocation funding on a quarterly basis" (DAF, 2005:9). Although these lines are taken from the most current version of AFI 21-103, the information is outdated. Since implementation of eLog21 (which we will discuss in detail later in this chapter), the MAJCOMs no longer set their own capability goals. Instead, the Air Force Directorate for Logistics, Installations & Mission Support (AF/A4/7) sets common capability standards for each weapon system (i.e., MDS) across active duty units and a complementary set of standards for guard and reserve units (Tyler, 2009).

In 2007, the Chief of Staff of the Air Force--Weapon System Review directed emphasis on AA instead of MC rates when assessing fleet health (Tyler, 2009). Shortly thereafter, AF/A4/7 developed a methodology for determining AA standards, given in equation 3.

$$AA\ Standard\ (\%) = \frac{PAI}{TAI} \times MC\ Standard \tag{3}$$

In this equation, primary aircraft inventory (PAI) is the number of aircraft assigned to a unit for the performance of its operational mission. The MC standard is based on the summation of MC hours required for all units to meet their operational, training, and test requirements (HQ AFMC/A4, 2009).

Since this equation is tied directly to MC rate standards, the value-added from this new metric is uncertain. Currently, AF/A4 is working on developing a new methodology with the goal of directly linking AA standards to readiness and decoupling AA from MC standards (Tyler, 2009).

Aircraft Sustainability Models and Aircraft Availability Forecasting Models

Over the years, the Air Force has used many different models to forecast MC and AA rates as well as the resources required to support its weapon systems. Although many of the models have been proven to provide useful results, there is currently no approved Air Force method to forecast MC or AA rates (OSD, 2009). We examine several of the prevailing models in order to gain an understanding of the techniques and variables that are used, as well as to see what role, if any, O&M costs have played.

Logistics Composite Model

Created in the late 1960s, the Logistics Composite Model (LCOM) is a "stochastic, discrete-event simulation that relies on probabilities and random number generators to model scenarios in a maintenance unit by manipulating certain variables" (Cole et al., 2007:1). Although the LCOM can calculate the resources required to support a weapon system at a given capability level (defined as sortie generation) considering a variety of variables, it is most prominently used by the Air Force to determine manpower levels in operational maintenance units. Specifically, the LCOM is used by the MAJCOMs to establish 65-70% of their maintenance manpower requirements (Cole et al., 2007). On the other hand, the LCOM does not directly consider the O&M funds needed to support a weapon system.

Aircraft Sustainability Model

The Aircraft Sustainability Model (ASM) is used to determine the number of spare parts required at Air Force bases and depots during wartime operations, peacetime operations, or combined operations. Given a desired level of aircraft availability or other readiness measure, the ASM specifies the exact quantity and optimal mix of spare parts in order to meet that goal. Logistics planners currently use the ASM for base-level applications such as calculating the spare parts needed to sustain a squadron of F-15s during a 60-day deployment in order to achieve an 80 percent AA rating at the end of day 60 (Blazer and Sloan, 2007). From our discussions with analysts currently working in the Air Force Materiel Command Cost Analysis (AFMC/FMC) office and the CAM office, we understand that this model does not inform enterprise level resource allocation decisions.

Mobility Aircraft Availability Forecasting Simulation Model

Beginning in 2003 and continuing through at least 2005, contractors from Northrop Grumman and Wright State University developed the Mobility Aircraft Availability Forecasting Simulation Model (MAAF) in response to the Air Mobility Command (AMC) Directorate of Logistics' request for a better forecasting tool. MAAF is an object-oriented modeling and simulation tool that is purportedly capable of predicting AA rates, providing "what if" analysis, and offering insight into problems that may affect AA (Wall, 2004; Ciarallo et al., 2005). Although the model proved to be a useful prototype in laboratory conditions, AMC determined the model was not ready for implementation in real-world operations.

Funding/Availability Multimethod Allocator for Spares

As recently as 2001, the Air Forced utilized the Funding/Availability Multimethod Allocator for Spares (FAMMAS) model to forecast MC rates for each mission design series (MDS) in its inventory. Employing time-series forecasting methods, FAMMAS uses the last three years of historical TNMCS and TNMCM data combined with past, present, and future spares funding to forecast MC rates. While it produces useful results, time-series models like FAMMAS do not provide insight into potential cause-and-effect relationships that may be exploited to affect MC rates. FAMMAS produces its forecasts by simply projecting data trends, not by using explanatory models. Furthermore, FAMMAS does not incorporate any operations, personnel, or environment-related variables in the model; it uses only TNMCS and TNMCM data that act as adjustment factors. Consequently, FAMMAS is not an effective tool to use for policy or resource decisions because of the limited scope of variables used in the model and because the relationships between the variables are largely unknown (Oliver, et al., 2001).

Aircraft Availability Model

Introduced as part of the Secondary Item Requirements System (D041 then, now D200A) in the late 1980s, the Aircraft Availability Model (AAM) is a tool that maximizes aircraft availability given some level of funding. Using marginal analysis, the AAM is able to build AA curves (see Figure 4) which can be used to prioritize funding for a given set of weapon systems (Blazer and Sloan, 2007). However, the AAM considers an aircraft available if it is not awaiting resupply of a spare part. This means that the model is only concerned with minimizing the TNMCS rate given some level of funding; it does not account for the other aspect of non-availability such as the NMCM, depot, or UPNR rates. The Air Force logistics community uses the model to compute the quantities needed for safety levels of the spare parts that it manages. The resulting safety levels become part of the overall requirement that drives budget requests, repair planning, and spare parts purchases (Hill, 2007).

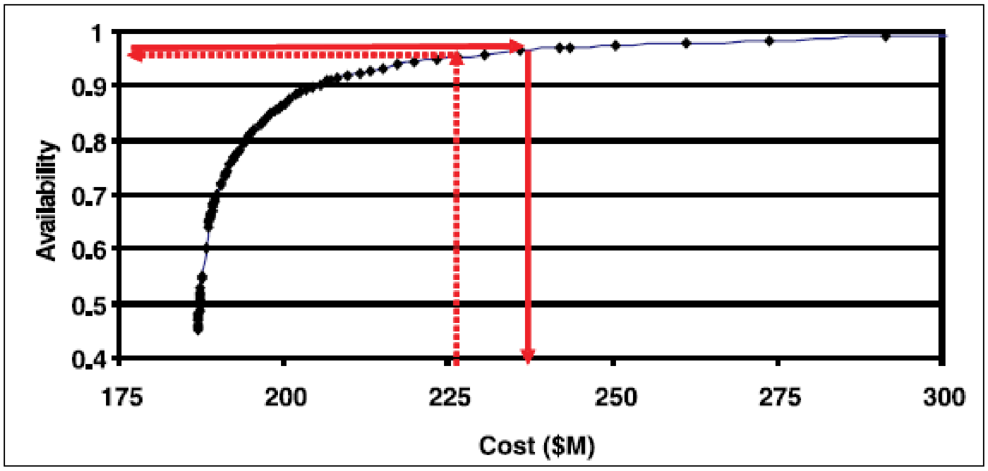


Figure 4: Aircraft Availability Curve (Blazer and Sloan, 2007)

Weapon System Sustainment Resource Allocation Process Prior to Centralized Asset Management

Prior to FY2008, the Air Force replicated the process to determine weapon system sustainment requirements, allocate resources, and execute funds across each of the ten MAJCOMS (including the Guard and Reserves) through stove-piped business areas. Figure 5 approximately represents this process. Requirements determination began with the MAJCOMS developing their individual requirements with input from AFMC product and logistics centers. Then, each MAJCOM created their budget and program objective memorandum (POM) inputs based on those requirements and submitted them to Air Staff

(Naguy and Keck, 2007). At this stage, requirements usually exceeded the resources available so resources were allocated on a "percent funded" basis (McKown, 2009). After enactment of funds, Air Staff sent funds to the MAJCOMS for execution. Finally, the MAJCOMS provided funds to the appropriate AFMC product and logistics centers for every program they operated on an expense-by-expense basis for execution. Additionally, product and logistics centers, depots, and supply operations exchanged funds within AFMC. As a result, over two million transactions occurred every year between AFMC's supply and maintenance activities alone (Naguy and Keck, 2007).

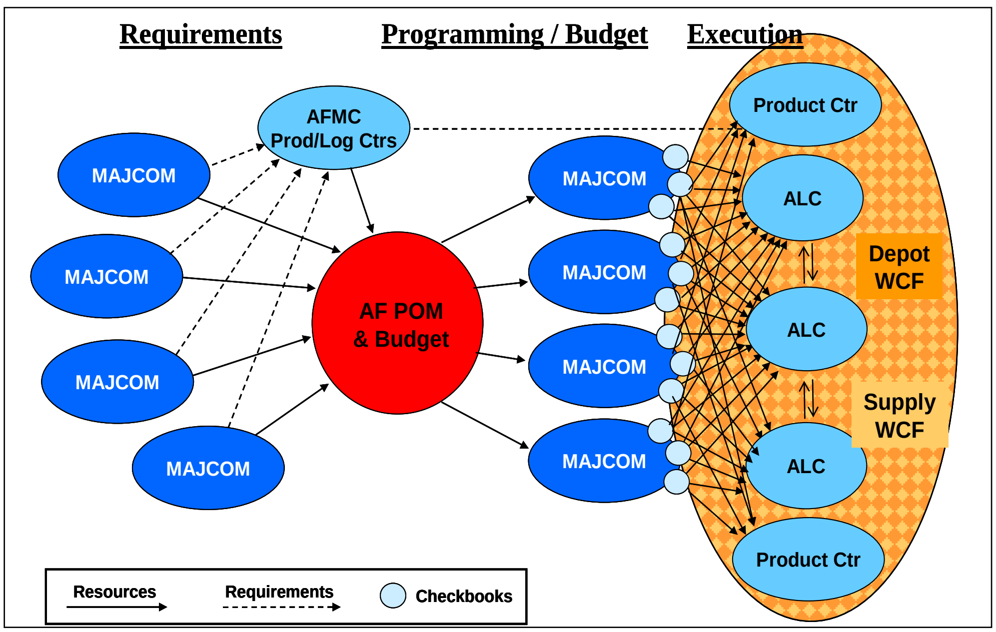


Figure 5: Pre-FY2008 Requirements Determination, Resource Allocation, & Execution Process (Naguy and Keck, 2007)

This process resulted in numerous inefficiencies, shortcomings, and unfavorable outcomes. Every command devoted significant time, money, and manpower into parallel activities. Since the process started at low organizational levels, the lead-time for formulating requirements was pushed well ahead of the execution of funds, which limited the flexibility of the entire process to respond to changing conditions. Next, because each of the commands was concerned with getting their fair share of the available sustainment funds, the process encouraged an adversarial relationship between the operating MAJCOMS, Air Staff and AFMC. Furthermore, since resources were traditionally allocated on a "percent funded" basis, MAJCOMs had an incentive to artificially inflate their actual requirements so that they might avoid receiving only a percentage of what they had requested (Naguy and Keck, 2007). Additionally, this practice of unconstrained requirements determination was left virtually unchecked because resource allocation was not based on performance (McKown, 2009).

Fleet management was possibly the biggest shortcoming of the old resource allocation process. In many cases, more than one MAJCOM operates a particular weapon system. As an example, six MAJCOMs currently fly the F-15. Under the old process, six operating MAJCOMs determined their requirements for their share of the F-15 fleet, but no single organization or individual was responsible for the resources necessary to support the fleet as a whole. As a result, one weapon system was "owned" by six separate entities, but no single entity had the scope or authority necessary to manage the entire fleet from a holistic perspective (Naguy and Keck, 2007).

Finally, due to the different procedures used and subsequent inconsistencies inherent in the requirements determination and resource allocation process, there was not a feasible way to determine the impact of funding reductions on aircraft availability. This shortcoming meant that Air Force leaders were unable to know if the needs of the warfighter were going to be met in an environment of constrained resources (McKown, 2009).

Expeditionary Logistics for the 21st Century and Centralized Asset Management

Given the myriad shortcomings of the status quo, the Air Force needed to find a better way of doing business. As a result of direction from Air Force leaders and consistent with the ubiquitous and overarching Air Force Smart Operations for the 21st Century (AFSO21) effort, the Air Force Logistics community developed eLog21 as a strategic action plan that seeks to "fundamentally change the way logistics is accomplished Air Force wide" (eLog21 Fact Sheet, 2009). According to the eLog21 fact sheet, the campaign is composed of a number of initiatives and ultimately strives to reach two goals: increase equipment availability to match aircraft availability (AA) targets, and reduce operations and support (O&S) costs by 10% (eLog21 Fact Sheet, 2009).

CAM is a specific eLog21 initiative undertaken jointly by AF/A4P, SAF/FMB and AFMC whose mission is to "centralize and integrate management of Air Force sustainment to optimize warfighting capability through effective and efficient allocation of resources across the enterprise" (Naguy and Keck, 2007:5). To achieve this mission, CAM centralizes programming, budgeting, and execution of weapon system resources within AFMC while standardizing and streamlining requirements determination for the Active Duty Air Force; currently, CAM does not manage weapon systems operating in Air Force Reserve Command (AFRC) or the Air National Guard (ANG). As a result, CAM provides the Air Force with an enterprise level view of its fleet, which makes it possible to maximize warfigthing capability through the optimization of aircraft availability (Naguy and Keck, 2007). In a nutshell, CAM was created to fix the burdensome requirements determination, resource allocation and execution process described in the previous section.

Beginning in fiscal year 2008, CAM implemented the new process depicted in Figure 6. Requirements determination begins with the lead MAJCOMs for each particular weapon system working with the additional user MAJCOMs to formulate total system requirements. Then, the lead MAJCOMs collaborate with AFMC product and logistics centers to finish developing and prioritizing requirements from an Air Force enterprise perspective. Once completed, AFMC submits a consolidated POM and budget request to Air Staff. Following enactment of funds, AFMC provides money directly to the appropriate product centers and logistics centers for execution. Finally, CAM has the ability to manage sustainment resource trade space throughout the year of execution because there are no longer multiple "owners" and multiple "checkbooks" being maintained by the MAJCOMs; resources are now holistically managed by the CAM office (Naguy and Keck, 2007).

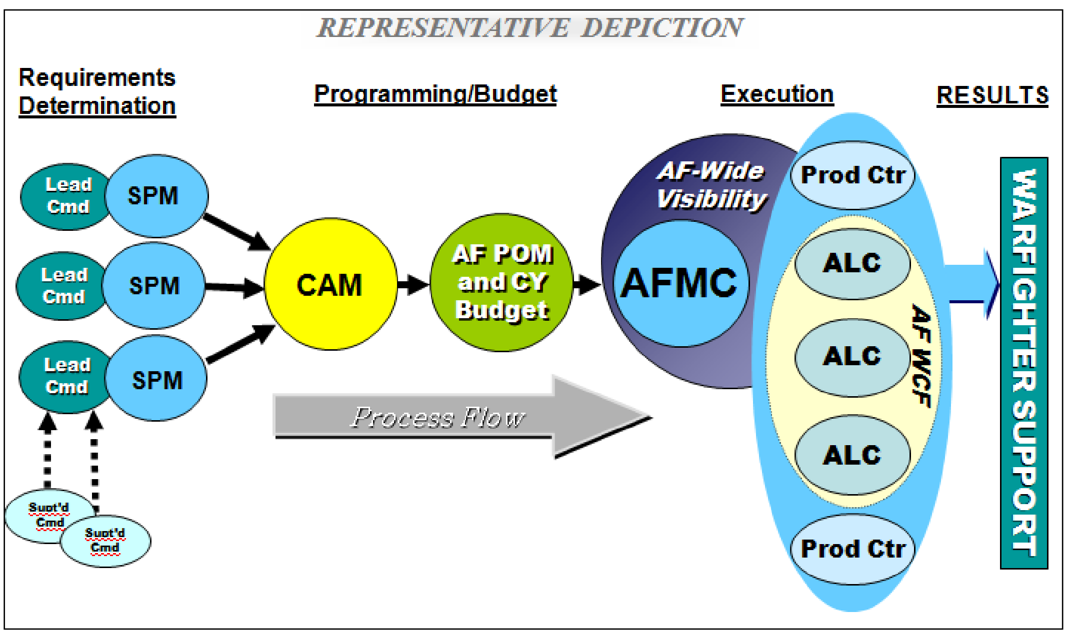


Figure 6: New Centralized Asset Management Process (Naguy and Keck, 2007)

We are interested in the new CAM process because it lays the foundation to provide the Air Force with the organizational structure necessary to holistically manage weapon systems. In other words, given this new process, the Air Force will be able to use O&M funding as a tool to optimize aircraft availability. However, the Air Force must use the correct metrics to measure weapon system availability and it must employ robust analytical tools to guide resource allocation decisions. We argue that the Air Force is using the correct metrics to measure weapon system availability; however, it does not currently have robust analytical tools or processes in place to guide its resource allocation decisions. Our research seeks to establish a definitive link between O&M costs and AA so that decision makers will have the information they need to optimize AA.

Chapter Summary

In previous sections, we discussed the importance of maintaining an adequate quantity of mission capable aircraft and provided an overview of the metrics used by the Air Force to assess the health of its fleet. We summarized the findings of previous research concerning that factors that may affect aircraft availability. Then, we provided an explanation of how the Air Force establishes AA rate standards. Next, we reviewed several models that have been developed and used by the Air Force to forecast AA rates. Finally, we detailed how the Air Force previously determined weapon system sustainment requirements, allocated resources, and executed funds. We explained how eLog21 and its subsequent initiative Centralized Asset Management have provided the organizational change necessary to allow the Air Force to manage its sustainment resources holistically. Despite the significant amount of research already accomplished, we find a significant gap concerning the relationship between O&M costs and AA, and thus see the need for further analysis.

III: Data Collection and Methodology

As we have shown in the literature review, a multitude of factors influence AA rates. Due to the complexity and numerous relationships that are possible among the factors, we collected data for an assortment of variables in order to build a dataset sufficient for constructing explanatory models. First, we explain the scope of our data collection and research. Second, we acknowledge the sources that we used to obtain the data. Third, we describe each of the variables while discussing the limitations within the dataset. Next, we describe how we analyze the variables in order to gain a better understanding of their characteristics and predictive ability. Finally, we discuss the methods that we use to build our explanatory models and generate results.

Scope of Data Collection and Research

The availability and reliability of data, specifically the data needed to capture O&M costs, determines the scope of our research. Much of the knowledge we rely on to make decisions regarding our cost data come from interviews with contractors who maintain the Air Force Total Ownership Cost (AFTOC) database and an AFTOC users' training workshop.

As we discussed in Chapter II, the scope of CAM's mission extends only to the Active Duty Air Force; it does not manage the O&M funds for weapon systems that operate in AFRC or ANG. For this reason, we only analyze Active Duty aircraft in our study because our ultimate goal is to advance the analytical capability of CAM by demonstrating a definitive link between O&M spending and AA. Additionally, research and development appropriations fund the majority of weapon systems operated by Air Force Materiel Command (AFMC), not O&M appropriations. Thus, we will not include any data attributable to aircraft assigned within AFMC.

At the beginning of FY1998, the Air Force made significant changes to accounting classifications, particularly those codes that capture costs related to flying operations. Therefore, our data collection begins with FY1998. The data maintained in AFTOC are subject to updates on a recurring basis as new information becomes available and corrections are made. Because of this, our last period of data is for the fourth quarter of FY08. We reason that data from this period should be static and no longer subject to significant updates or corrections. Finally, in an attempt to keep our definition of O&M costs standard across all MDS, we only evaluate organically maintained aircraft in our study. CLS maintained aircraft report their costs to different accounting classifications than organically maintained aircraft so the costs are not directly comparable.

Since we will analyze only Active Duty (excluding AFMC), organically maintained aircraft with data from 1998 – 2008, we can further narrow the scope of our research to MDS that fit this criteria. Specifically, we choose to analyze aircraft that have data available from 1998 – 2008, that are still in the active Air Force inventory, and that have a TAI of at least 19. Table 3 lists the MDS that we analyze in this study.

Table 3: List of MDS Chosen for Study

MDS	
A-10A	F-15E
OA-10A	F-16C
B-1B	F-16D
B-2A	KC-135R
B-52H	KC-135T
F-15C	T-38A
F-15D	T-38C

Data Sources and Variables

Data Sources

We obtained data for this study using three databases: the Logistics Installations and Mission Support – Enterprise View (LIMS-EV) database, the AFTOC management information system, and the Reliability and Maintainability Information System (REMIS). Created as an eLog21 initiative, LIMS-EV provides a single point of entry to a variety of legacy data systems such as REMIS and the Multi-echelon Resources and Logistics Network (MERLIN). LIMS-EV allows users to acquire standardized data and tracks metrics, trends, and results (LIMS-EV Fact Sheet, 2010). We found the AA, aircraft age, TAI, and cannibalization data using LIMS-EV. AFTOC is a tool that integrates cost, logistic, and personnel data from more than a dozen legacy systems into a single format. In order to present useful, coherent data, AFTOC assigns (or allocates when required) the data to weapon systems, bases, and MAJCOMs according to standard business rules (AFTOC, 2009). Our O&M cost and personnel data came from the AFTOC database. REMIS is the Air Force's primary database for aircraft usage data. Similar to LIMS-EV and AFTOC, REMIS interfaces with a variety of other systems to provide consolidated data (Oliver, 2001). We used REMIS to retrieve our data for flying hours, sorties, and landings.

Dependent Variable: Aircraft Availability

Our goal in this study is to develop explanatory models that will demonstrate a definitive link between O&M costs and AA. Thus, AA will serve as our dependent variable. We retrieved our data from LIMS-EV at the MDS level, by MAJCOM, by fiscal year quarter. AA is most commonly expressed as a rate; however, we also obtained

AA data in the form of the average number of available aircraft and the total number of available hours. Table 4 shows an example of this data.

Table 4: Subset of Normalized Aircraft Availability Data from LIMS-EV

FY	Q	MAJCOM	MDS	AA Rate	AA #	AA Hrs
1998	Q1	ACC	A-10	0.725	117	259,244
1998	Q2	ACC	A-10	0.671	109	234,876
1998	Q3	ACC	A-10	0.692	112	243,984
1998	Q4	ACC	A-10	0.703	113	249,375
1999	Q1	ACC	A-10	0.705	108	237,482
1999	Q2	ACC	A-10	0.668	101	218,402
1999	Q3	ACC	A-10	0.679	103	224,156
1999	Q4	ACC	A-10	0.722	107	235,702

Independent Variable: O&M Costs

Our primary independent variable of interest in this study is O&M costs. Specifically, we are interested in those costs that can be directly attributed to supporting the flying operations of a given MD or MDS. For this reason, the availability and reliability of data for this variable determine the scope of our research.

Element of Expense/Investment Code (EEIC) 644, also known as Material Support Division (MSD), contain costs directly associated with the flying hour program. Costs for EEIC 644 can be further disaggregated by transaction type. Fly-depot level repairables (DLRs) are recorded as transaction type XD2, consumable items are coded XB3, and base level repairable items are labeled XF3. Transactions may occur as charges or credits; however, our data only consider the resulting net costs. Additional consumable costs are found in EEIC 609 (General Supply Division), but these costs are not considered because their range extends far beyond flying operations. Furthermore, EEIC 645 contains other DLR costs, but we exclude these costs from our study as well because they are not “fly-DLRs.” It is also worth noting that CLS costs are accounted for in EEIC 578, but as we mentioned previously, CLS aircraft will not be included in our research. Our study only considers those costs contained in EEIC 644 because it represents the segment of O&M costs that are directly attributable to flying operations.

EEIC 644 costs in AFTOC are simultaneously allocated to the MDS they were used to support, indicated by the "Mission Design Series—Standard Reporting Designator (MDS SRD)" column heading, in addition to the weapon system whose program element code (PEC) was used to pay the bill, reflected by the "Mission Design—Cost Analysis Improvement Group (MD CAIG)" column heading. In the majority of circumstances these two fields match, in which case there is no problem. When the MDS SRD field does not match the MD CAIG field, we simply allocate the dollars to the weapon system identified in the MDS SRD field because that is the system supported by the expenditure. However, two cases arise that force us to make some judgmental allocations based on the information available. When the MDS SRD field contains "null" (no data entered), we look to the MD CAIG field for information. If there is a weapon system identified in the MD CAIG field, we allocate the costs to that weapon system as the next best alternative based on the advice of contractors who maintain the AFTOC database. In the rare cases where both fields are "null," we discard the data since we have no means of identifying the correct MDS. Table 5 shows an example of the raw cost data retrieved from AFTOC.

Table 5: Subset of Raw Cost Data from AFTOC

FY	QTR	CAIG	MAJCOM	MDS SRD	MD CAIG	ERRC	Net Cost
1999	Q3	2.3.1	USAFE	KC-135T	KC-135R	XD2	$13,930.53
1999	Q4	2.3.1	ACC	NULL	NULL	XB3	$19,703.22
1999	Q4	2.3.1	ACC	NULL	KC-135R	XF3	$1,117.90
1999	Q4	2.3.1	ACC	A-10	A-10	XB3	$154,744.15
1999	Q4	2.3.1	ACC	A-10	A-10	XD2	$20,138,457.23
1999	Q4	2.3.1	ACC	A-10	A-10	XF3	$855,392.66
1999	Q4	2.3.1	ACC	A-10	F-15E	XD2	$3,294.48
1999	Q4	2.3.1	ACC	A-10	F-16C/D	XB3	$1,683.69
1999	Q4	2.3.1	ACC	A-10	F-16C/D	XD2	$694,477.35

The cost data for the weapon systems we evaluate include 11,745 rows of data. MDS SRD contains 3,593 values that are "null" (30.6% of the data); however, only 174 entries contain "null" in both MDS SRD and MD CAIG (1.5% of the data). This means that we relied on our allocation heuristic to account for 29.1% of the cost data and we discarded an additional 1.5% of the data.

As a final means of normalizing the data, we used inflation rates approved by the Office of the Secretary of Defense to convert all costs to CY08$.

Additional Independent Variables

In order to have adequate information to build explanatory models, we collected data on variables that have been shown in previous research to have predictive ability with respect to AA. The following sections detail our remaining independent variables.

Usage Variables. We obtained quarterly flying hour, sortie, and landing data for each MDS, by MAJCOM from the REMIS database. REMIS assigns the data both to the command that owns the aircraft, and to the command that is operating the aircraft. As one would expect, the owning command and the operating command are the same in the vast majority of situations. However, circumstances arise where one unit may loan aircraft to another unit for a given period. In this situation, we ignore the operating command and allocate the usage data to the command possessing the aircraft. This heuristic follows the same logic we discussed previously concerning the allocation of O&M cost data. Table 6 shows an example of the raw usage data obtained from REMIS.

Table 6: Subset of Raw Usage Data from REMIS

FY	System	Operating_Agency	Poss_Cmd	FHQ4	SortiesQ4	LandingsQ4
FY2007	F-15D	PACAF	PACAF	392.0	265	266
FY2007	F-15D	USAFE	USAFE	109.1	85	87
FY2007	F-16C	ACC	ACC	7,855.7	5,582	5,585
FY2007	F-16C	AETC	AETC	6,027.4	4,622	4,631
FY2007	F-16C	AFRC	ACC	886.7	593	593
FY2007	F-16C	PACAF	PACAF	9,999.7	5,339	5,357
FY2007	F-16C	USAFE	USAFE	6,228.8	4,181	4,181
FY2007	F-16D	ACC	ACC	957.8	690	690

Inventory Variables. LIMS-EV contains data for average aircraft age, average airframe hours, TAI, and PAI. As we discussed in Chapter II, TAI and PAI are two different concepts. However, through conversations with LIMS-EV customer support representatives and analysts in the AF/A4LY (Weapons System Division), we learned that LIMS-EV does not reflect these terms accurately. At the time of this writing, data provided from LIMS-EV under the column heading TAI is erroneous and the actual TAI is represented under the "Poss'd" column heading. With that said, we acquired quarterly data for TAI and monthly data for average age and average airframe hours for each MDS, by MAJCOM. In order to remain consistent with the periods of data we collected for the other independent variables and the dependent variable, we translate the monthly data into quarterly periods by using only the observations for the last month of each quarter (December, March, June, and September). Admittedly, we could have averaged the data over each quarter to achieve the same objective, but for ease of computation and data aggregation, we took the former approach. Furthermore, average age exhibits a perfect linear trend over time, which means our analysis is not affected by the choice we made in normalizing our data. Table 7 shows an example of the raw inventory data from LIMS-EV.

Table 7: Subset of Raw Inventory Data from LIMS-EV

Command	MDS	Month-Year	TAI	Avg Airframe Hours	Avg Age of Fleet
ACC	A010A	OCT-2005	88	8583.3	24.22
ACC	A010A	NOV-2005	88	8622.7	24.31
ACC	A010A	DEC-2005	88	8662.5	24.4
ACC	A010A	JAN-2006	88	8696.3	24.48
ACC	A010A	FEB-2006	88	8725.4	24.55
ACC	A010A	MAR-2006	88	8759.1	24.63
ACC	A010A	APR-2006	88	8789.5	24.72
ACC	A010A	MAY-2006	88	8820.1	24.81

Maintenance Variables. We retrieved maintenance data from LIMS-EV that represent the various states of disrepair aircraft may be coded. Specifically, we collected data on cannibalization hours and the five possible statuses of non-available aircraft, which are the depot, NMCM, NMCS, NMCB, and UPNR rates. We do not include the variables representing non-availability in our models since they would not provide any useful explanatory information, but we do use cannibalization hours as an independent variable. Although cannibalization hours represent non-availability, the practice of cannibalizing aircraft is a proven method of providing necessary parts to other aircraft in the fleet (Oliver, 2001).

Personnel Variables. AFTOC maintains annual data on the actual number of personnel assigned to support a given MDS by AFSC for both officers and enlisted. We obtained data reflecting specifically maintenance personnel for our study. We further disaggregated the data by separating the data for officers from enlisted and also grouping the enlisted data by skill level (1, 3, 5, 7, 9, or 0). Enlisted personnel typically enter a career field as a skill level one and progress upwards based on their time served in that field and their demonstrated level of expertise; chief master sergeants are automatically designated as skill level zero. Disaggregating the data in this manner allows us to analyze more relationships such as the effect that higher proportions of low skill level maintainers have on AA rates. In order to translate the annual periods into quarterly periods, we reason that the number of assigned personnel fluctuates little over the course of a year so we simply use the annual figures for all four quarters of the year. Table 8 shows an example of the raw personnel data retrieved from AFTOC.

Table 8: Subset of Raw Personnel Data from AFTOC

FY	CAIG	COMMAND	MDS	AFSC	AFSC_COUNT
FY1998	1.2	ACC	A-10A	2W151	109.4859
FY1998	1.2	ACC	A-10A	2W171	43.1567
FY1998	1.2	ACC	A-10A	2W191	7.3694
FY1998	1.2	ACC	B-1B	2A000	1
FY1998	1.2	ACC	B-1B	2A000	2
FY1998	1.2	ACC	B-1B	2A031	54.75
FY1998	1.2	ACC	B-1B	2A051	0.75
FY1998	1.2	ACC	B-1B	2A051	58

Dummy Variables: Location, Season, and Aircraft Characteristics. We created dummy variables to represent the location, season, and characteristics of our MDS. We use four location dummy variables to represent the five MAJCOMs and three seasonal dummy variables to represent the four quarters in our study. We also create dummy variables to represent each of the MDS groups and aircraft types in our study.
Table 9 provides a list of the dummy variables we created.

Table 9: List of Dummy Variables

MAJCOM	Quarter	MDS Group	Aircraft Type
AETC	Q2	B-1B	Bomber
AMC	Q3	B-2A	Fighter/Attack
PACAF	Q4	B-52H	Heavy
USAFE	(Quarter 1 is the base case)	F-15C/D	(Trainers are the base case)
(ACC is the base case)		F-15E	
		F-16C/D	
		KC-135	
		T-38	
		(The A-10 group is the base case)	

Data Aggregation

Our data can be analyzed on three separate dimensions: 1) type of aircraft, 2) level of assignment of aircraft, and 3) units of time. First, it is possible to aggregate aircraft data at a high level based on aircraft type (e.g. fighter or bomber) or at lower levels such as MD (e.g. F-15 or A-10) or MDS (e.g. F-16C or F-15E). In his dissertation published by RAND in 2008, Lt Col Eric Unger argued that O&M costs at the MDS level in AFTOC suffer from data validity concerns. Specifically, he found that some costs were allocated from the MD level to the MDS level based on proportion of flying hours instead of actual expenditures for each MDS within the given MD. Consequently, some data may be misallocated within the MD and using the data in explanatory models would result in an overstatement of the relationship between flying hours and costs (Unger, 2008). Therefore, we evaluate aircraft at the MDS level only where AFTOC properly allocates costs.

In his 2008 AFIT thesis, 1Lt Tyler Hess created cost forecasting models for the Air Force flying hour program. His research built on Unger's findings such that he was able to analyze aircraft at the lowest possible level while still maintaining proper cost allocation. We build on Hess's research and use the same MDS groupings that he proved properly represented O&M costs (Hess, 2009). Table 10 shows the MDS in our study and their final MDS grouping for our research.

Table 10: Assignment of MDS to MDS Groups

MDS	MDS Grouping
A-10A, OA-10A	A-10
B-1B	B-1B
B-2A	B-2A
B-52H	B-52H
F-15C, F-15D	F-15C/D
F-15E	F-15E
F-16C, F-16D	F-16C/D
KC-135R, KC-135T	KC-135
T-38A, T-38C	T-38

Second, our data can be analyzed at different levels of aggregation based on location. For example, data can be acquired as low as the base level, it can be aggregated to the MAJCOM level, or it can be further aggregated and analyzed at the Air Force level. Hess found that analyzing cost and usage data at the base level presents construct validity concerns. The crux of his argument was that costs are often misallocated at the base level of aggregation because organizations often pay for things that go towards supporting aircraft that they do not own. By moving from the base to the MAJCOM level of aggregation, we are able to avoid much of the misallocation (Hess, 2009). Thus, we choose to analyze our data at the MAJCOM level of aggregation for location.

Time is the final dimension for which our data can be aggregated. Typically, data are available in monthly, quarterly, or annual periods. In order to have sufficient data points for our analysis, we collected our data at the quarterly level of aggregation.

Final Database

Once our data was normalized and aggregated at the quarterly level, we used Microsoft Excel® and Microsoft Access® to create our final database. Table 11 shows selected variables from the final database.

Table 11: Subset of Variables from Final Database

FY	Q	MAJCOM	MDS	AA Rate	Total EEIC 644	Fly Hrs	Sorties	Landings	TAI	Avg Age	CANN Hrs
1998	Q1	ACC	A-10	0.725	14,727,747	15,556	7,978	7,978	162	16	3,617
1998	Q2	ACC	A-10	0.671	18,755,389	15,845	8,352	8,372	162	17	3,643
1998	Q3	ACC	A-10	0.692	20,649,961	17,120	8,674	8,687	161	17	4,642
1998	Q4	ACC	A-10	0.703	26,734,875	16,147	7,942	7,944	153	17	3,933
1999	Q1	ACC	A-10	0.705	12,622,025	13,367	7,095	7,096	152	17	3,909
1999	Q2	ACC	A-10	0.668	18,801,395	14,280	7,646	7,646	152	18	3,750
1999	Q3	ACC	A-10	0.679	22,469,193	14,346	7,211	7,250	151	18	4,668
1999	Q4	ACC	A-10	0.722	26,007,053	13,642	7,210	7,311	144	18	4,534

Variable Analysis Methodology

Because of the large number of independent variables we obtained data for, we must investigate the potential predictive ability between each of them and the dependent variable before we attempt to build models. Furthermore, we are interested in accounting for the possibility that lagging relationships may exist between the independent variables and the dependent variables. To test for this condition, we lag each independent variable with respect to time one to four quarters into the future. These variables will depict the relationship between an independent variable in one quarter and the dependent variable in future quarters.

Correlation analysis is a convenient technique for expediently examining the linear relationships between variables. Using JMP® release seven, we are able to construct a multivariate matrix that shows the linear relationship between every combination of two variables. We use the correlation coefficient, which is a measure of linear dependency between two variables on a negative one to one scale, to determine the degree of correlation between any two of the variables. Coefficients with an absolute value of one prove a perfect linear relationship between two variables (Wooldridge, 2006).

In addition to providing insight into which variables will be useful in explanatory models, correlation analysis will help us identify potential cases of multicollinearity. Multicollinearity refers to a correlation between independent variables in a multiple regression model (Wooldridge, 2006). Because instances of multicollinearity add confusion to a model by making it difficult to interpret the contribution of the independent variables, we avoid it by not including pairs of variables in our models where multicollinearity exists. In order to identify specific cases of multicollinearity, we use JMP® to calculate variance inflation factors (VIF) for the independent variables in our models. In practice, acceptable VIF levels are generally less than or equal to five or ten. When VIF levels exceed these thresholds, it is a sign that a high degree of multicollinearity exists for two or more of the independent variables. For our analysis, we accept VIF measures of less than or equal to five.

We also examine the distribution of the data for each of our variables to determine if there is a need to perform discrete analysis. Random variables that show irregular patterns in their data may provide better predictive ability if the data is categorized into discrete values (Wooldridge, 2006). In such cases, we create dummy variables to represent the discrete data.

Model Building Methodology

Since we have numerous variables that may prove to be explanatory in predicting AA, we use multiple regression analysis to create our models. Briefly stated, multiple regression allows us to simultaneously control for many variables when explaining the response. In our case, this is an important attribute because we will be able to investigate the affect O&M costs have on AA, while controlling for several other factors at the same time.

Ordinary Least Squares (OLS) is the most commonly used method for estimating the parameters of the regression model and it is the method we use in our study. OLS estimates the parameters by minimizing the sum of squared errors between the actual and predicted values of the model (referred to as the residuals). OLS provides the best linear unbiased estimator for the parameters, given the assumptions of this technique are met. We discuss the assumptions later in this chapter.

In a general form, multiple regression equations take the following structure:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon \tag{4}$$

Where:

Y = dependent variable
$x_1, x_2, \ldots x_k$ = independent variables
β_0 = the intercept
$\beta_1, \beta_2, \ldots \beta_k$ = the population coefficients
ε = the random error component

Our models are constructed in this fashion such that AA is explained to the maximum extent possible. To guide our analysis, we use the five steps outlined below for building valid, useful models (McClave et al., 2008:666):

Step 1: Hypothesize the deterministic component of the model. This component relates the mean, *E(y)*, to the independent variables x_1, x_2, … x_k. This involves the choice of the independent variables to be included in the model.

Step2: Use the sample data to estimate the unknown model parameters β_0, β_1, β_2, … β_k in the model.

Step 3: Specify the probability distribution of the random error term, ε, and estimate the standard deviation of this distribution, σ.

Step 4: Check that the assumptions on ε are satisfied, and make model modifications if necessary.

Step 5: Statistically evaluate the usefulness of the model.

Testing Regression Assumptions

Step four in the model building process outlined previously requires that the assumptions of the random error term, ε, are satisfied. The assumptions refer to the probability distribution of ε and are given as follows (McClave et al., 2008:667):

Assumption 1: Mean equal to zero.

Assumption 2: Variance equal to σ^2 (also known as constant variance or homoscedasticity).

Assumption 3: Normal distribution.

Assumption 4: Random errors are independent (in a probabilistic sense).

The validity of our models relies, in part, on the random error term meeting the assumptions outlined above. We provide verification of the assumptions for all of our models and discuss deviations from the assumptions in Chapter IV.

In order to check that the first assumption is met, we rely on visual inspection of a plot of the residuals about a mean line of zero. We test for compliance with the second assumption by visually analyzing the residual by predicted plots to determine whether any irregular patterns of variance are present. In addition, we use the Breusch-Pagan test to statistically determine whether homoscedasticity exists. For this test, small p-values reject the null hypothesis of constant variance; therefore, large p-values are desired. We test the third assumption by plotting the studentized residuals in a histogram for visual examination, followed by statistical validation using the Shapiro-Wilk test. Similar to the Breusch-Pagan test, large p-values are preferred so that we may accept the null hypothesis of normality. Failure to meet the fourth assumption is caused by autocorrelation of the residuals, meaning each residual is affected by the previous one. We check for autocorrelation by analyzing a plot of the residuals by row in order to see if any trends are obvious. We further test this assumption using the Durbin-Watson test which tests for autocorrelation at lag one. Empirical evidence shows that data for AA rates may be subject to positive autocorrelation (high residuals tend to be followed by high residuals, and negative residuals tend to be followed by negative residuals) (Oliver, 2001). Given this knowledge, we use a left-tailed test for positive autocorrelation and reject the null hypothesis of independence whenever p-values are less than 0.05.

In addition to the assumptions already discussed, we analyze every data point in our models using the Cook's D Influence statistic. This statistic measures the influence a given data point has on the overall model. For our analysis, we specify large Cook's D measures as those values over 0.5. In cases where a data point has a Cook's D value greater than 0.5, we re-run the model with that data point excluded in order to determine whether it should remain in the model. If there are no significant changes to the p-values of the overall model or individual parameter p-values, we allow the data point to remain in the model. Additionally, we attempt to provide an explanation for why the data point was influential.

Model Validation

In order to determine the robustness of the predictive ability of our explanatory models, we must validate our models. To do this, we set aside the final 9 quarters of data from our original dataset (20 percent) while building our models. Once our models are complete, we combine the independent variable data from the final nine quarters with the data used to build the model. The dependent variable data for the last nine quarters remains excluded so that when the model is run in JMP®, we are able to generate prediction intervals for each of those quarters. Finally, we are able to determine if the actual values of the dependent variable for the nine quarters fall within the prediction interval in addition to comparing the actual values to the values predicted by the model. Using this procedure for model validation allows us to evaluate our model's usefulness when new data from outside the original sample is used for prediction.

Chapter Summary

In Chapter III, we outlined the scope of our research effort and detailed the data we use to perform our analysis. We explained the statistical techniques we use to investigate the predictive ability of our data and construct our explanatory models. Lastly, we described how we test that the assumptions of our regression models are satisfied and how we validate the models' usefulness. In the next chapter, we describe our analysis and detail the results.

IV: Analysis and Results

Using the methods described in the previous chapter, we discuss our analysis and the results of our study in Chapter IV. First, we outline the challenges presented by our data and the techniques we use to overcome the problems. Next, we evaluate the models created for each of the MDS in our study. Finally, we summarize our results and discuss other techniques that we explore for establishing a relationship between O&M costs and AA.

Adjustments to Data Required for Analysis

We begin by estimating models for each MDS by MAJCOM with AA hours as the dependent variable and total EEIC 644 costs, flying hours, sorties, landings, TAI, and average age as the independent variables. Not surprisingly, we encounter problems with multicollinearity for several of the independent variables. Table 12 is a correlation matrix of the variables in the model for ACC F-15C/Ds. Although the data is different for every MDS and MAJCOM, the data we show for ACC F-15C/Ds is representative of the correlations we find with nearly all of the other MDS in our study. Thus, we use this regression output as an example to explain the common problems encountered with all of the MDS in our study.

Table 12: Correlation Matrix of Variables for ACC F-15C/Ds

	AA Hrs	Total EEIC 644	Fly Hrs	Sorties	Landings	TAI	Avg Age
AA Hrs	1.0000	0.2620	0.8293	0.8727	0.8722	0.8940	-0.5135
Total EEIC 644		1.0000	0.1047	0.2348	0.2344	0.1924	0.1589
Fly Hrs			1.0000	**0.8633**	**0.8637**	0.8808	-0.7820
Sorties				1.0000	**1.0000**	0.8755	-0.6050
Landings					1.0000	0.8752	-0.6057
TAI						1.0000	-0.7489
Avg Age							1.0000

Due to their obvious operational relationships, flying hours, sorties, and landings exhibit very high degrees of correlation. In fact, sorties and landings are perfectly correlated for this dataset as exhibited with a correlation coefficient of 1.00, while flying hours yields correlation coefficients of 0.8633 and 0.8637 with sorties and landings, respectively (highlighted in bold in Table 12). Additionally, we calculate VIF scores for these three variables as shown in Table 13; all measures exceed our threshold of five.

Table 13: VIF Scores for Usage Variables in Initial ACC F-15C/D Model

Term	VIF
Fly Hrs	7.455
Sorties	66724.138
Landings	66644.096

Therefore, we determine that it would be unwise to include more than one of the usage variables in our models since doing so would make it difficult to interpret the contribution of each variable to the model. As a rule, we elect to use flying hours as our usage variable of choice in all models where it demonstrates predictive ability.

Next, we see that changes in TAI over time in our dataset result in overstated relationships between AA hours and nearly all of the independent variables in our dataset, except average age. The reason for this is simple. TAI fluctuates as the result of several factors such as organizational or mission changes within operational Air Force units and the retirement or acquisition of new aircraft. When these events occur, it is natural for other changes to take place such as movement of personnel and resources. If the number of aircraft is reduced, it follows that the number of operators and maintainers will decrease as well, resulting in fewer flying hours and fewer total available hours. In order to address this problem, we convert all of our variables, with the exception of average age, into a rate of some kind. AA is commonly expressed as a percentage so it makes sense to use the AA rate as our dependent variable. For all of our independent variables (except age), we divide each data point by TAI which results in variables represented as a "per-aircraft" rate. This procedure results in variables that show genuine relationships in our models and allow for direct comparison across MAJCOMs and MDS.

Explanatory Models

Using the model building process outlined in the previous chapter, we developed models for 16 of our 22 MDS by MAJCOM by quarter datasets. Of those 16 models, only 2 found EEIC 644 costs as a predictive variable. Nonetheless, we discuss the four best models in detail (those with an adjusted R^2 of greater than 0.70), and then summarize the remaining models. Appendix A contains a complete review of our results.

KC-135 by AMC by Quarter

Table 14 highlights the summary statistics of our model for KC-135 aircraft in Air Mobility Command (AMC). Only flying hours per TAI and the dependent variable lagged one period are included as independent variables. We utilize the dependent variable lagged one period in this model because without it we notice first order autocorrelation with a Durban-Watson statistic of 0.46, which is significant at the 0.01

level. Additionally, the model's adjusted R^2 falls from 0.86945 to 0.51178 without the lagged dependent variable included in the model.

Prior to accepting this specification as a useful model, we verified that the assumptions of normality, constant variance, and independence were met as described in the previous chapter. Additionally, we checked for influential data points using the Cook's D test and found that no observations were influential. We provide the results of our diagnostic tests for this model in Appendix B.

Table 14: KC-135 (AMC) Explanatory Model

Summary of Fit					
R^2	0.87736				
Adjusted R^2	0.86945				
Root Mean Square Error	0.02655				
Mean of Response	0.60528				
Observations (or Sum Wgts)	34				
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**	
Model	2	0.15627	0.07813	110.887	
Error	31	0.02184	0.00070	**Prob > F**	
C. Total	33	0.17812		<.0001	
Parameter Estimates					
Term	**Estimate**	**Std Error**	**t Ratio**	**Prob>|t|**	**VIF**
Intercept	0.12256	0.04113	2.98	0.0056	
FlyHrs/TAI	0.00061	0.00015	3.99	0.0004	1.807
1QLagAARate	0.67384	0.08413	8.01	<.0001	1.807

To test the robustness and validity of the model, we include the final nine periods of independent variable data and run the model in JMP®. This process generates individual prediction intervals for the dependent variable at each of the nine periods. Theoretically, our model should be able to predict AA rates within the prediction intervals (at 95% confidence) 95% of the time. We show the results of this analysis in Table 15 and Figure 7.

Table 15: KC-135 (AMC) Sensitivity Analysis

FY-Q	Lower 95% Confidence	Observed AA Rate	Predicted AA Rate	Upper 95% Confidence	Absolute Percent Error
2006-Q4	0.6524	0.6875	0.7095	0.7666	3.19%
2007-Q1	0.6294	0.6235*	0.6854	0.7414	9.91%
2007-Q2	0.5908	0.6223	0.6474	0.7039	4.02%
2007-Q3	0.6029	0.6436	0.6618	0.7208	2.83%
2007-Q4	0.6285	0.6351	0.6892	0.7500	8.53%
2008-Q1	0.6104	0.6337	0.6686	0.7268	5.50%
2008-Q2	0.6168	0.6112*	0.6767	0.7366	10.72%
2008-Q3	0.6035	0.6619	0.6652	0.7268	0.49%
2008-Q4	0.6487	0.6454*	0.7108	0.7729	10.14%
*Observations fall outside prediction interval					MAPE = 6.15%

Although this was our best model with respect to the adjusted R^2 value, empirical results show that the observed AA rates fell within the prediction interval only 66.7% of the time. We should also note that the prediction intervals had an average range of 0.12, which means that our model should predict AA rates within a window of 12 percentage points. Given that this could mean the difference between achieving a stated goal for AA or falling well short, the prediction interval range produced by our model may be too large to be useful for Air Force decision makers. Additionally, the mean absolute percent error (MAPE) for this model was 6.15%.

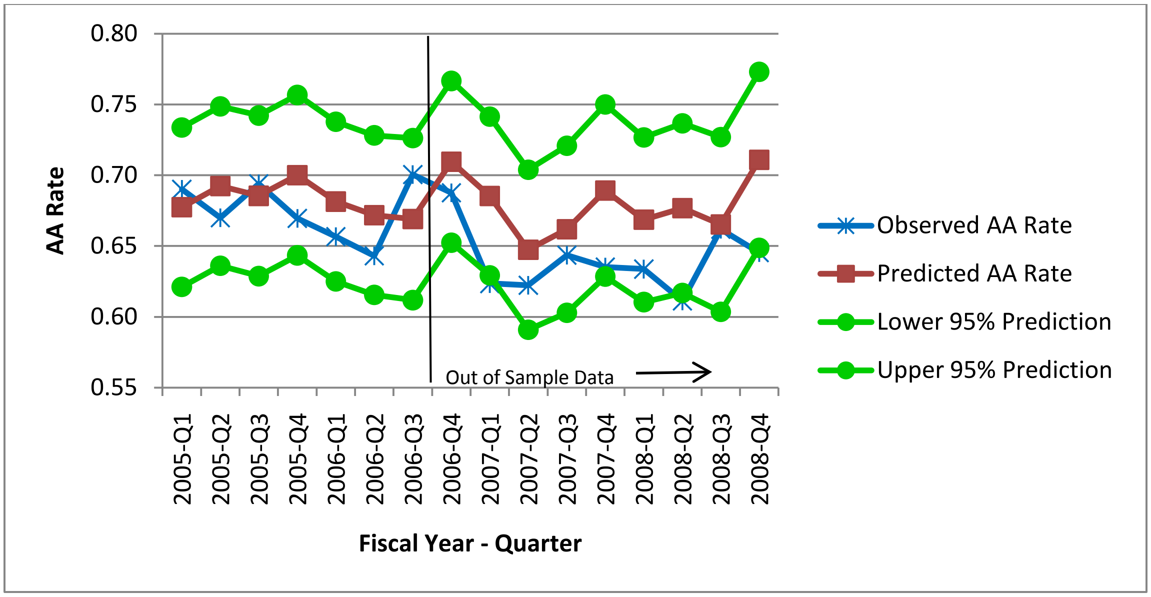


Figure 7: KC-135 (AMC) Sensitivity Analysis

Figure 7 is useful because it visually shows the trend of AMC KC-135 AA rates over the last four years. We can see that the AA rates observed during the last nine quarters are mostly lower than previous quarters. Additionally, our model failed to predict this trend. One possible reason is that the range of independent variable data used to produce the model does not reflect the range of data used to validate the model. As a rule, a model's usefulness will suffer if it is used to predict a response outside the range of data from which it was created. Specifically, the data we used when constructing the model for the flying hours per TAI variable ranged from a low of 67.6 to a high of 184.9. However, the data used for this variable when we validated the model exceeded this threshold seven times with values ranging from 187.9 to 232.4. We show the ranges of independent variable data in Appendix C.

F-15E by ACC by Quarter

Our next model is for F-15Es in Air Combat Command (ACC). Table 16 shows the summary statistics, which include an adjusted R^2 of 0.80918. We use cannibalization hours per TAI, the total number of 1-, 3-, and 5-level maintainers per TAI, and the dependent variable lagged one period as independent variables. Again, we include the lagged dependent variable in this model because without it we notice first order autocorrelation with a Durban-Watson statistic of 1.46, which is significant at the 0.05 level. Moreover, the model's adjusted R^2 drops to 0.75472 without the lagged dependent variable included in the model.

Just as we did with the first model, we verified that the assumptions of normality, constant variance, and independence were met, in addition to checking for influential data points. Yet again, all assumptions were satisfied.

Table 16: F-15E (ACC) Explanatory Model

Summary of Fit					
R^2	0.82653				
Adjusted R^2	0.80918				
Root Mean Square Error	0.01708				
Mean of Response	0.67059				
Observations (or Sum Wgts)	34				
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**	
Model	3	0.04173	0.01391	47.647	
Error	30	0.00875	0.00029	**Prob > F**	
C. Total	33	0.05049		<.0001	
Parameter Estimates					
Term	**Estimate**	**Std Error**	**t Ratio**	**Prob>|t|**	**VIF**
Intercept	0.31488	0.08637	3.65	0.0010	
1QLagAARate	0.38525	0.12231	3.15	0.0037	2.555
CANNhrs/TAI	-0.00105	0.00022	-4.73	<.0001	2.228
1,3,5_SkillLvl/TAI	0.01015	0.00454	2.23	0.0333	1.274

Using the same process as before, we test the validity of our model by including the final nine periods of independent variable data and running the model in JMP®. Table 17 and Figure 8 provide the results of this analysis.

Table 17: F-15E (ACC) Sensitivity Analysis

FY-Q	Lower 95% Confidence	Observed AA Rate	Predicted AA Rate	Upper 95% Confidence	Absolute Percent Error
2006-Q4	0.6689	0.6740	0.7050	0.7412	4.61%
2007-Q1	0.6735	0.6788	0.7141	0.7547	5.20%
2007-Q2	0.6742	0.7108	0.7128	0.7514	0.28%
2007-Q3	0.6870	0.6899	0.7248	0.7625	5.05%
2007-Q4	0.6792	0.6632*	0.7184	0.7575	8.32%
2008-Q1	0.6679	0.5930*	0.7085	0.7490	19.47%
2008-Q2	0.6310	0.6737	0.6801	0.7292	0.95%
2008-Q3	0.6741	0.6918	0.7141	0.7541	3.22%
2008-Q4	0.6797	0.6324*	0.7181	0.7564	13.55%
*Observations fall outside prediction interval					MAPE = 6.74%

Our model for F-15Es in ACC performs nearly as well as our first model. Again, six out of nine (66.7%) observations fall within the prediction interval; however, the MAPE is slightly larger at 6.74%. Furthermore, the range of our prediction intervals is smaller than the first model with an average of 0.08 (i.e., 8% in terms of the AA rates).

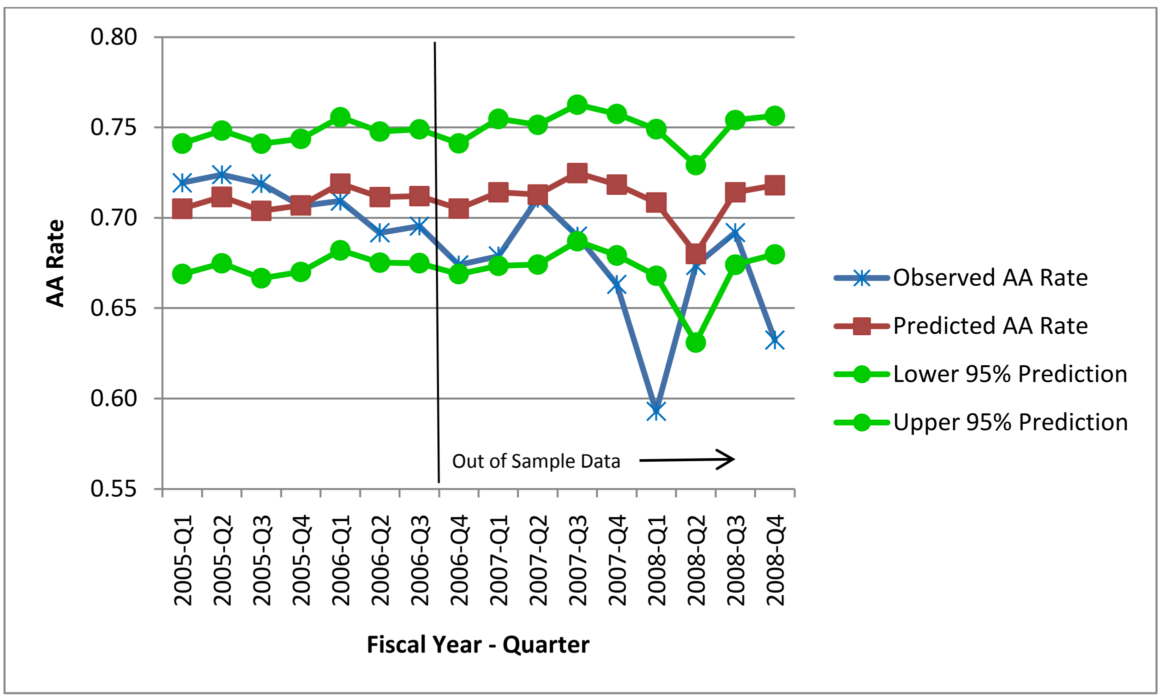


Figure 8: F-15E (ACC) Sensitivity Analysis

Figure 8 shows a sharp decrease in the AA rate during the first quarter of 2008 that our model did not predict. In our model's defense, this observation may be considered somewhat of an outlier. After mechanical failure resulted in the crash of an Air National Guard F-15C on November 2, 2007, the Air Force grounded all F-15 models until an investigation was conducted. Later, on November 15, 2007, the Air Force began lifting the restriction for F-15Es after they concluded that the E-model was not susceptible to the same failure. Nonetheless, F-15Es were still grounded for at least 13 days which resulted in a low AA rate for the first quarter of 2008 (Wicke, 2007). Finally, we must consider that the independent variable data used to validate the model fell outside the range of data used to construct the model six times for the cannibalization hours per TAI variable and once for the total number of 1-, 3-, and 5-level maintainers per TAI variable.

B-1 by ACC by Quarter

Our third model is for B-1 aircraft in ACC. Table 18 provides the summary statistics for this model. We use the three regressors from the first two models, in addition to the dependent variable lagged one period as independent variables for our B-1 model. Due to first order autocorrelation as evidenced by a Durban-Watson statistic of 0.75 (significant at the 0.01 level), we included the lagged dependent variable. Additionally, the model's adjusted R^2 decreases from 0.76778 to 0.61946 without the lagged dependent variable included in the model. Interestingly, the coefficient for the total number of 1-, 3-, and 5-level maintainers per TAI is negative in this equation where it was positive in the model for F-15Es. We suspect that as the total number of lower skilled maintainers reaches a tipping point, they begin to adversely affect AA rates, especially if the total number of highly skilled maintainers does not increase at the same rate. In this situation, the total number of maintainers may be constant, but the proportion of low-skill maintainers will be increasing.

As we did with the first two models, we verified that the assumptions of normality, constant variance, and independence were met, in addition to checking for influential data points. Here again, all assumptions were fulfilled.

Table 18: B-1 (ACC) Explanatory Model

Summary of Fit					
R^2	0.79593				
Adjusted R^2	0.76778				
Root Mean Square Error	0.03423				
Mean of Response	0.50145				
Observations (or Sum Wgts)	34				
Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**	
Model	4	0.13255	0.03313	28.278	
Error	29	0.03398	0.00117	**Prob > F**	
C. Total	33	0.16654		<.0001	
Parameter Estimates					
Term	**Estimate**	**Std Error**	**t Ratio**	**Prob>|t|**	**VIF**
Intercept	0.54769	0.14720	3.72	0.0008	
FlyHrs/TAI	0.00177	0.00067	2.61	0.0141	3.672
CANNhrs/TAI	-0.00139	0.00043	-3.23	0.0031	3.705
1,3,5_SkillLvl/TAI	-0.01053	0.00378	-2.78	0.0094	5.148
1QLagAARate	0.61311	0.13618	4.50	0.0001	2.579

Once again, we test the validity of our model by including the final nine periods of independent variable data and running the model in JMP®. Table 19 and Figure 9 provide the results of this analysis.

Table 19: B-1 (ACC) Sensitivity Analysis

FY-Q	Lower 95% Confidence	Observed AA Rate	Predicted AA Rate	Upper 95% Confidence	Absolute Percent Error
2006-Q4	0.5419	0.5267*	0.6217	0.7014	18.02%
2007-Q1	0.5316	0.5265*	0.6246	0.7177	18.64%
2007-Q2	0.5404	0.5202*	0.6414	0.7424	23.29%
2007-Q3	0.5339	0.5120*	0.6338	0.7337	23.78%
2007-Q4	0.4975	0.5194	0.5790	0.6605	11.49%
2008-Q1	0.5459	0.5003*	0.6526	0.7593	30.45%
2008-Q2	0.5241	0.4302*	0.6264	0.7287	45.62%
2008-Q3	0.4723	0.3644*	0.5835	0.6947	60.14%
2008-Q4	0.4205	0.3373*	0.5426	0.6647	60.89%
*Observations fall outside prediction interval					MAPE = 32.48%

Immediately we find that only one out of nine observations fell within the prediction interval generated by our model. The failure of our model is magnified when we consider that the average range of our prediction intervals was nearly 0.20 (i.e., 20% in terms of the predicted AA rates). Lastly, our model produced a MAPE of 32.48%.

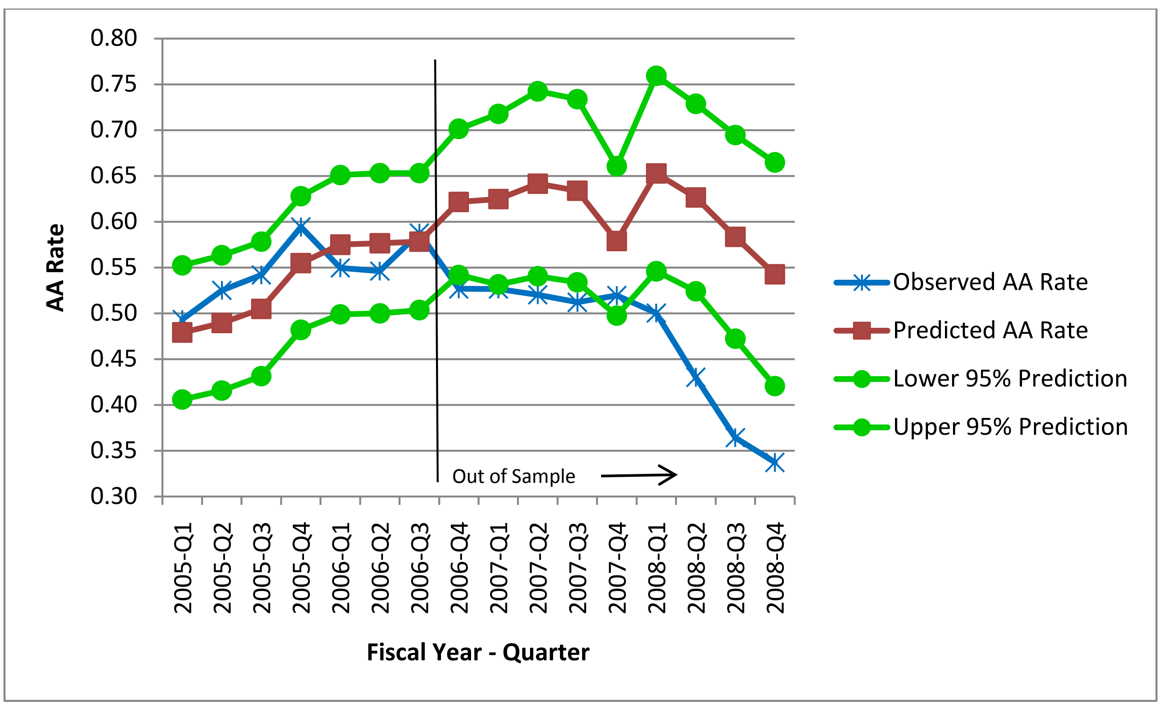


Figure 9: B-1 (ACC) Sensitivity Analysis

Figure 9 plainly shows that B-1s experienced a steady and dramatic decline in AA rates during the time period used to test our model, but we were unable to find a definitive reason as to why this trend occurred. According to Air Force officials, the decline in AA rates is simply a sign of deterioration on individual components, not an indication of a specific problem (Rolfsen, 2008). Additionally, the data used for our variables to validate the model fell within the original range of data in every instance with the exception of the data used for cannibalization hours per TAI, which used four observations below the original range of data. This suggests that something related to B-1 AA rates fundamentally changed during the final nine periods; however, we were unable to capture this change with the variables for which we had data.

KC-135 by AETC by Quarter

The last model we will discuss is for KC-135s in Air Education and Training Command (AETC). As shown in Table 20, this model is the first for which we are able to use total EEIC 644 costs (lagged one period) as an independent variable. We also use average aircraft age and the lagged dependent variable as regressors in this model. Again, we must include the lagged dependent variable because without it we see first order autocorrelation given by a Durban-Watson statistic of 0.82 (significant at the 0.01 level). Furthermore, the adjusted R^2 drops from 0.70286 to 0.51723 without the AA rate lagged one period included in the model.

Lastly, we verified that the assumptions of the random error term were satisfied, in addition to checking for influential data points. Like the first three models, all assumptions were met.

Table 20: KC-135 (AETC) Explanatory Model

Summary of Fit						
R^2	0.72987					
Adjusted R^2	0.70286					
Root Mean Square Error	0.04218					
Mean of Response	0.73629					
Observations (or Sum Wgts)	34					
Analysis of Variance						
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**		
Model	3	0.14427	0.04809	27.0198		
Error	30	0.05339	0.00178	**Prob > F**		
C. Total	33	0.19767		<.0001		
Parameter Estimates						
Term	**Estimate**	**Std Error**	**t Ratio**	**Prob>|t|**	**VIF**	
Intercept	-0.15297	0.11357	-1.35	0.1881		
TotalEEIC644/TAI (Lag 1)	4.473E-07	2.272E-07	1.97	0.0583	1.022	
Avg Age	0.01082	0.00359	3.01	0.0052	1.584	
1QLagAARate	0.56119	0.12435	4.51	<.0001	1.575	

Once more, we test the validity of our model by including the final nine periods of independent variable data and running the model in JMP®. Table 21 and Figure 10 provide the results of this analysis.

Table 21: KC-135 (AETC) Sensitivity Analysis

FY-Q	Lower 95% Confidence	Observed AA Rate	Predicted AA Rate	Upper 95% Confidence	Absolute Percent Error
2006-Q4	0.7718	0.8492	0.8643	0.9569	1.78%
2007-Q1	0.7770	0.7876	0.8702	0.9633	10.49%
2007-Q2	0.7163	0.7464	0.8097	0.9032	8.48%
2007-Q3	0.7033	0.7576	0.7977	0.8921	5.30%
2007-Q4	0.7239	0.7715	0.8186	0.9132	6.10%
2008-Q1	0.7301	0.8416	0.8251	0.9200	1.97%
2008-Q2	0.7517	0.7724	0.8494	0.9471	9.97%
2008-Q3	0.7174	0.7834	0.8167	0.9160	4.25%
2008-Q4	0.7427	0.7310*	0.8408	0.9389	15.01%
*Observation falls outside prediction interval					MAPE = 7.04%

Although eight out of nine observations fall within the prediction interval, we can attribute some of this success to the fact that our model produced prediction intervals with an average range of 0.19. Such a large range when forecasting AA rates make this model's usefulness questionable. Finally, the MAPE for this model is 7.04%.

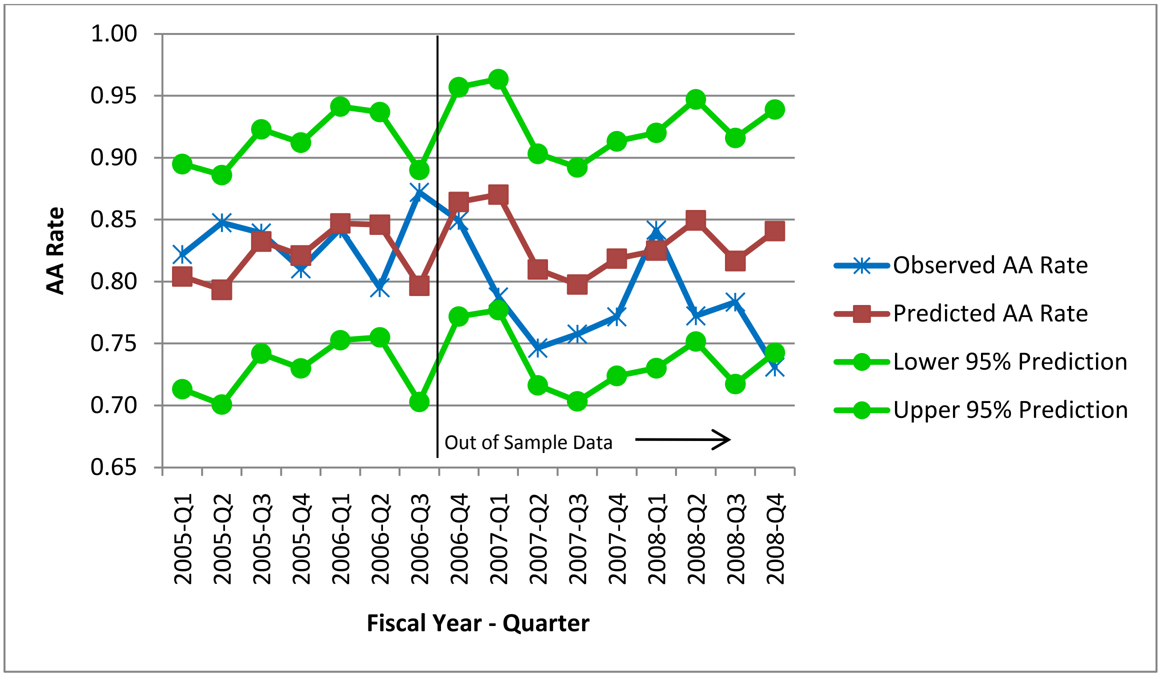


Figure 10: KC-135 (AETC) Sensitivity Analysis

Summary of Remaining Models

Table 22 summarizes the remaining models to include the adjusted R^2 values, variable coefficients, and failed assumptions that we were unable to avoid. In cases where we collected data on MDS that operate in more than one MAJCOM (e.g., A-10, F-15E), we attempted to develop models that would be useful in predicting AA rates for the entire fleet of aircraft across each MAJCOM. However, due to the apparent differences in predictive variables, we were unable to produce useful models for an MDS across all of its MAJCOMs. It goes without saying, therefore, that we were unable to develop useful models to represent more than one MDS.

Table 22: Summary of Models Created for Remaining MDS and MAJCOMs

MDS	MAJCOM	Adj R^2	n	1QLag AARate	FlyHrs/ TAI	Avg Age	EEIC644/ TAI (Lag 1)	1,3,5/7,9,0 Skill Level Ratio (note 1)	Total Maintainers/ TAI	Other Variables	Failed Assumptions (see codes below)
A-10	PACAF	0.55399	34	0.39325	-	-	-	-0.06561	-	0.04166 (note 2)	none
A-10	ACC	0.52320	34	0.66465	0.00117	-	-	-	-	-	none
A-10	USAFE	0.40542	34	0.38250	-	-	-	0.05395	-	-	none
B-2	ACC	0.45791	35	-	0.00145	-	-	0.13274	-	-	none
B-52	ACC	0.30829	34	0.45696	-0.00074	-	-	-	-	-	none
F-15C/D	ACC	0.65512	35	-	0.00189	0.01215	-	-	-	-	none
F-15C/D	AETC	0.41891	34	0.45637	-	-	1.0203E-07	-	-	-	A (note 3)
F-15C/D	PACAF	-	-	-	-	-	-	-	-	-	-
F-15C/D	USAFE	-	-	-	-	-	-	-	-	-	-
F-15E	USAFE	-	-	-	-	-	-	-	-	-	-
F-16C/D	ACC	0.68421	34	0.49512	-	-	-	-0.04230	0.00843	-	none
F-16C/D	PACAF	0.63977	33	0.80798	-	-	-	-	-	-0.02696 (note 4)	D (note 5)
F-16C/D	AETC	0.41748	35	-	-	-	-	-	0.01518	-	A (note 6)
F-16C/D	USAFE	-	-	-	-	-	-	-	-	-	-
KC-135	PACAF	0.49527	34	0.41306	0.00179	0.01975	-	-0.09711	-	-	none
KC-135	USAFE	-	-	-	-	-	-	-	-	-	-
T-38	AETC	0.63190	34	0.64955	-	0.00371	-	-	-	-	D (note 7)
T-38	ACC	-	-	-	-	-	-	-	-	-	-

Failed Assumptions: (A) Normality; (B) Constant Variance; (C) Independence; (D) Influential Data Points
Notes: 1.) This variable represents the ratio of 1-, 3-, and 5-level maintainers to 7-, 9-, and 0-level maintainers. 2.) A dummy variable to represent the 3rd Quarter of each fiscal year demonstrated predictive ability. 3.) The model failed the Shapiro-Wilk test for normality with a p-value of 0.0429. 4.) A dummy variable to represent the 4th Quarter of each fiscal year demonstrated predictive ability. 5.) An influential data point was removed from the model because it significantly changed p-values. 6.) The model failed the Shapiro-Wilk test for normality with a p-value of 0.0332. 7.) An influential data point was allowed to remain in the model because the model was not changed when it was removed.

Further Analysis

Given our inability to develop regression models that show a definitive relationship between O&M costs and AA rates using our preferred strategy, we explore two more techniques.

During our review of the data, we notice that there is a high level of O&M costs recorded in EEIC 644 in the fourth quarter of each year for almost every MDS and MAJCOM (when compared to the previous quarters of the same fiscal year). An example of this trend is shown in Figure 11 for the A-10 in ACC. This occurrence is not surprising since units often have to spend their remaining funds at a higher rate at the end of a fiscal year. Accordingly, this phenomenon should make it possible for us to test our hypothesis that increased spending leads to higher AA rates. In order to test our theory, we use dummy variables to represent each quarter of the fiscal year in our regression model. If there is a statistically significant difference between one of the quarters and the other three, we will see this in the form of a low p-value and a significant independent variable in our model. We repeat this process several times in order to allow each quarter to serve as the baseline and include various combinations of the dummy variables representing each quarter in our model. However, multiple attempts using this technique for every MDS and MAJCOM failed to show any significant difference from one quarter to the next.

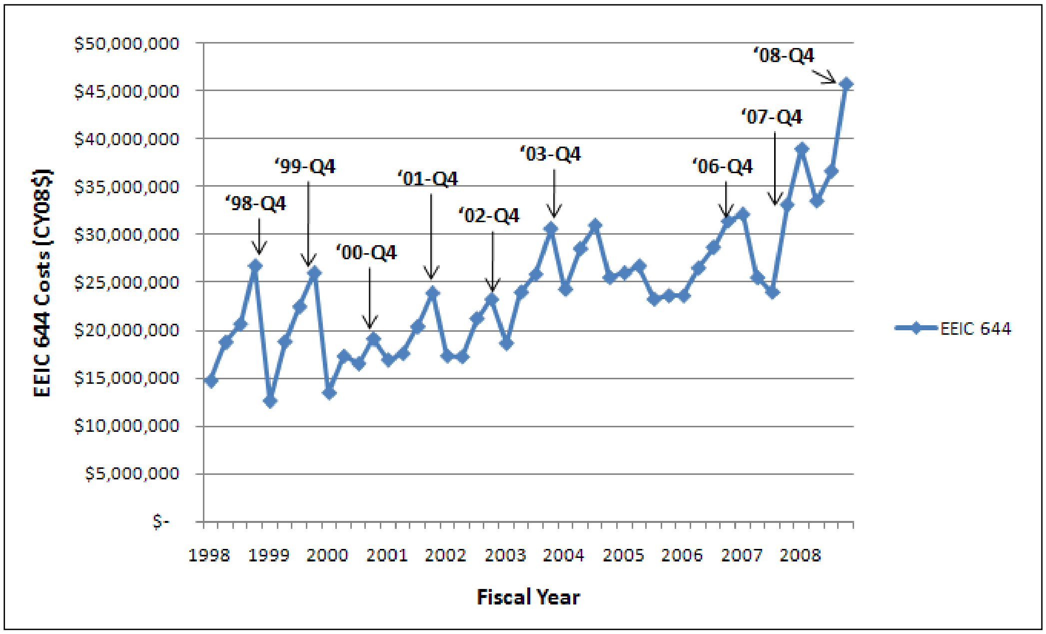


Figure 11: A-10 (ACC) EEIC 644 Costs by FY Quarter

For our next attempt at modeling AA rates using O&M costs, we take a different approach and use two of the variables representing non-availability as the dependent variable in our regression models. First, we use the NMCS rate as the dependent variable in order to see if we can model the percentage of aircraft that are not mission capable for supply reasons. Second, we use the NMCM rate as the dependent variable and attempt to model the percentage of aircraft that are not mission capable for maintenance reasons. If we are able to produce predictive models that explain either NMCS or NMCM, we will be able to extract results that are nearly as useful as modeling AA rates directly. However, using these metrics as dependent variables does not produce better models.

Chapter Summary

In Chapter IV, we explained the challenges presented by our data and the techniques we used to overcome these difficulties. Next, we detailed the results of our four best explanatory models and summarized the remaining models. Finally, we explored two other techniques for examining our data, but with only marginal success.

In the next chapter, we use our findings to address our research questions. Then, we discuss policy implications and the strengths and limitations of our study as well as opportunities for further research.

V: Conclusions

In this chapter, we provide answers to our research questions based on the results of our study. Next, we discuss potential policy implications. Finally, we highlight the strengths and limitations of our study while suggesting areas for further research.

Research Questions

1. What variables are significant predictors of AA rates?

Of the 16 models we developed, we find that the dependent variable lagged one period is a significant predictor in 13 of our models. Admittedly, this variable was included primarily to help mitigate the negative effects of autocorrelation in the residuals, and its explanatory contribution is of limited usefulness to decision makers. By definition, we must have the current period's AA rate in order to forecast the next period's AA rate. This requirement makes it very difficult for the models to be useful beyond one period into the future.

Next, we find that the flying hours per TAI variable is a predictive independent variable in seven of our models. For all but one, the coefficient is positive which suggests that flying aircraft more often increases the AA rate. The coefficient is only negative for the B-52 by ACC by quarter model.

Finally, our results show that the variable representing the ratio of 1-, 3-, and 5-level maintainers to 7-, 9-, and 0-level maintainers is predictive in five of our models; however, the coefficients are mixed. Three models show negative coefficients, which imply that larger numbers of low skilled maintainers decrease the effectiveness of the maintenance being performed, resulting in lower AA rates. The other two models result in positive coefficients, which imply the opposite effect. Intuitively, this makes less sense. We hypothesize that where positive coefficients are found, this variable is reflecting some other effect such as larger numbers of maintainers in general.

2. Are AA rates influenced by changes in O&M spending?

From the analysis we performed, we are unable to show that AA rates are significantly influenced by changes in the amount of O&M spending. Using total EEIC 644 costs as our variable to represent O&M spending, we find that it is predictive in only 2 of our 16 models (12.5%). Both the KC-135 by AETC by quarter model and the F-15C/D by AETC by quarter model found total EEIC 644 costs to be useful in predicting AA rates.

3. Do the AA rates of some weapon systems respond to changes in O&M costs more than others?

Our models indicated that AA rates of only the KC-135 in AETC and the F-15C/D in AETC responded to changes in O&M spending. Given our limited findings, we are unable to determine if the AA rates of some weapon systems respond to changes in O&M spending more than others.

4. Can a single model be developed to represent multiple MDS?

Despite repeated attempts, we were unable to develop a model that would represent multiple MDS or multiple MAJCOMs for a single MDS. The models we created are specific to a particular MDS and MAJCOM.

5. Can the models produced by this research be used as an effective decision tool for the Centralized Asset Management (CAM) office?

Given our lack of findings with respect to O&M costs and AA, we do not believe that the CAM office would find our models useful for allocating resources. With more research, we hope that models will be developed that shed light on the relationship between O&M costs and AA rates.

Policy Implications

As we discussed in Chapter II, CAM is significantly changing the way Air Force maintenance organizations acquire and pay for parts and supplies. Instead of purchasing items at the base level, CAM now centrally manages the process for all active duty units. Although we previously focused on the many positive attributes of the new process, we must consider the potential negative consequences of centralization. Before CAM was implemented, base level maintenance organizations were incentivized to be fiscally responsible. They were constrained by their base level budget, which encouraged them to be cost effective and repair parts which could be redeemed for credits to pay for other items. Now that funds are centrally managed, the Air Force must ensure that base level maintenance organizations continue to operate responsibly. If base level organizations no longer feel constrained by their local budgets, they may begin to operate in a less cost effective manner resulting in higher overall costs to the Air Force.

Strengths, Limitations, and Further Research

Although our research failed to draw a definitive link between O&M costs and AA rates, the data we collected and the variables we used in our study were reliable. Our data was extracted directly from official Air Force databases and we used extreme care when compiling our database. Furthermore, we carefully analyzed our variables and incorporated them in our models in a fashion that would not result in disingenuous findings.

We chose total costs recorded in EEIC 644 to represent O&M costs because we were able to show a clear link between the money spent and the aircraft type supported. In hindsight, this may have been a weakness in our analysis. The CAM office manages a large portfolio of funds for the Air Force. Figure 12 shows the funding posture for FY2010, which totals $12,363.1 million. Budgeted at $2,147.8 million, EEIC 644 accounts for nearly half of the flying hour program; however, we can plainly see that the majority of O&M costs managed by CAM are not represented by our variable. We suggest that further research be done to include Depot Purchased Equipment Maintenance (EEICs 540, 541, 542, 543, 544, 545, 546, 548, and 549), Sustaining Engineering (EEIC 583), Technical Orders (EEIC 594), and Flying Hour Program costs (EEICs 605, 609, 61952, 69302, and 699 in addition to EEIC 644).

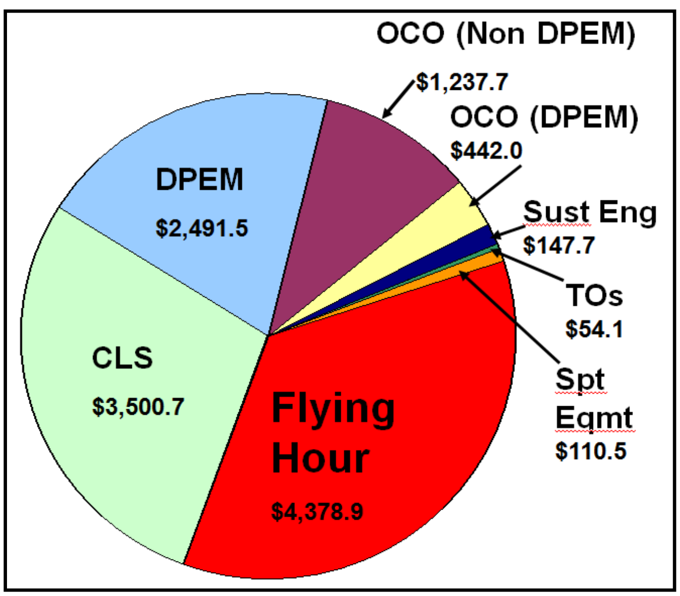


Figure 12: CAM FY2010 Funding Posture (in millions, BY10$)

We selected our range of data to include FY1998 – 2008 because we were able to ensure consistent accounting of EEIC 644 costs during that timeframe. Given several more years of post-CAM data (FY2008 and beyond), we feel that this study may produce entirely different results. As we discussed in Chapter II, the resource allocation process prior to CAM was not designed to manage weapon systems from a performance-based perspective. Now that the Air Force is operating with CAM and a philosophy of "performance-based logistics," we hypothesize that a study done in the future would yield more useful and interesting results.

Appendix A: Summary of Results for All Models

Summary of Regression Coefficients and Adjusted R^2 Values

MDS	MAJCOM	Adj R^2	n	1QLag AARate	FlyHrs/ TAI	Avg Age	EEIC644/ TAI (Lag 1)	CANNhrs/ TAI	1,3,5_SkillLvl/ TAI	1,3,5/ 7,9,0 Skill Level Ratio (note 1)	Total Maintainers/ TAI	Other Variables	Failed Assumptions (see codes below)
A-10	PACAF	0.55399	34	0.39325	-	-	-	-	-	-0.06561	-	0.04166 (note 2)	none
A-10	ACC	0.52320	34	0.66465	0.00117	-	-	-	-	-	-	-	none
A-10	USAFE	0.40542	34	0.38250	-	-	-	-	-	0.05395	-	-	none
B-1	ACC	0.76779	34	0.61311	0.00177	-	-	-0.00139	-0.0105	-	-	-	none
B-2	ACC	0.45791	35	-	0.00145	-	-	-	-	0.13274	-	-	none
B-52	ACC	0.30829	34	0.45696	-0.00074	-	-	-	-	-	-	-	none
F-15C/D	ACC	0.65512	35	-	0.00189	0.01215	-	-	-	-	-	-	none
F-15C/D	AETC	0.41891	34	0.45637	-	-	1.0203E-07	-	-	-	-	-	A (note 3)
F-15C/D	PACAF	-	-	-	-	-	-	-	-	-	-	-	-
F-15C/D	USAFE	-	-	-	-	-	-	-	-	-	-	-	-
F-15E	ACC	0.80918	34	0.38525	-	-	-	-0.00105	0.01015	-	-	-	none
F-15E	USAFE	-	-	-	-	-	-	-	-	-	-	-	-
F-16C/D	ACC	0.68421	34	0.49512	-	-	-	-	-	-0.04230	0.00843	-	none
F-16C/D	PACAF	0.63977	33	0.80798	-	-	-	-	-	-	-	-0.02696 (note 4)	D (note 5)
F-16C/D	AETC	0.41748	35	-	-	-	-	-	-	-	0.01518	-	A (note 6)
F-16C/D	USAFE	-	-	-	-	-	-	-	-	-	-	-	-
KC-135	AMC	0.86945	34	0.67384	0.000612	-	-	-	-	-	-	-	none
KC-135	AETC	0.70286	34	0.56119	-	0.01082	4.4731E-07	-	-	-	-	-	none
KC-135	PACAF	0.49527	34	0.41306	0.00179	0.01975	-	-	-	-0.09711	-	-	none
KC-135	USAFE	-	-	-	-	-	-	-	-	-	-	-	-
T-38	AETC	0.63190	34	0.64955	-	0.00371	-	-	-	-	-	-	D (note 7)
T-38	ACC	-	-	-	-	-	-	-	-	-	-	-	-

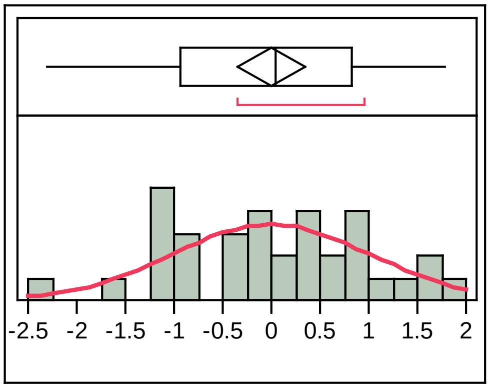
Failed Assumptions: (A) Normality; (B) Constant Variance; (C) Independence; (D) Influential Data Points

Notes: 1.) This variable represents the ratio of 1-, 3-, and 5-level maintainers to 7-, 9-, and 0-level maintainers. 2.) A dummy variable to represent the 3rd Quarter of each fiscal year demonstrated predictive ability. 3.) The model failed the Shapiro-Wilk test for normality with a p-value of 0.0429. 4.) A dummy variable to represent the 4th Quarter of each fiscal year demonstrated predictive ability. 5.) An influential data point was removed from the model because it significantly changed p-values. 6.) The model failed the Shapiro-Wilk test for normality with a p-value of 0.0332. 7.) An influential data point was allowed to remain in the model because the model was not changed when it was removed.

Appendix B: Sample of OLS Regression Diagnostic Tests

KC-135 by AMC by Quarter Model

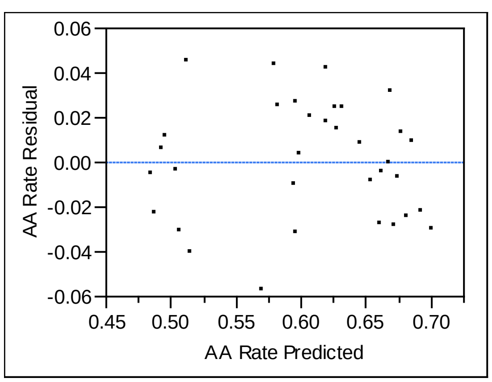
First, we show a histogram of studentized residuals followed by the Shapiro-Wilk Test for normality. The null hypothesis is that the residuals come from a normal distribution; small p-values reject the null hypothesis. Alpha is 0.05 for all tests.



Shapiro-Wilk Test

W	Prob<W
0.9768	0.6704

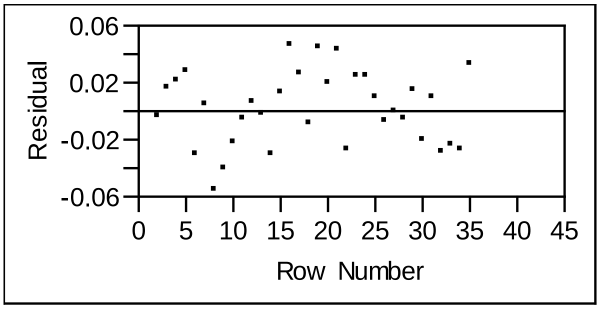
Next, we show the residual by predicted plot and the Breusch-Pagan test for constant variance of the residuals. The null hypothesis is that the residuals exhibit constant variance; small p-values reject the null hypothesis.



Breusch-Pagan Test

p-value	0.678

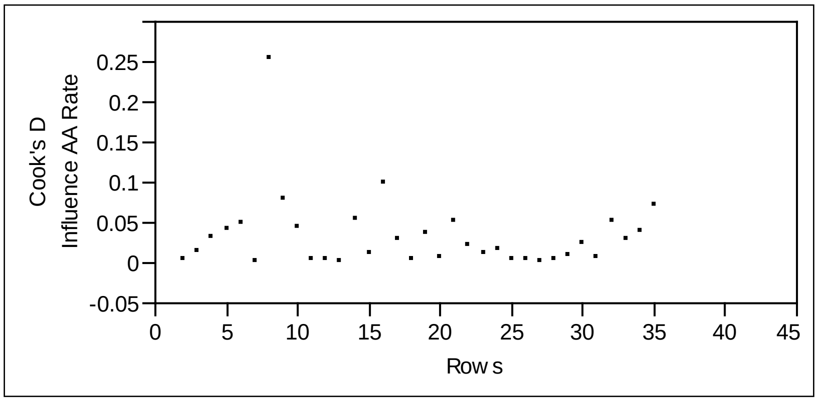
Third, we show the residual by row plot and the Durbin-Watson test for autocorrelation. The null hypothesis is that the residuals are not serially correlated; small p-values reject the null hypothesis.



Durbin-Watson Test

Durbin-Watson	Number of Obs.	AutoCorrelation	Prob<DW
1.6044	34	0.1747	0.0704

Last, we show the Cook's Distance plot for influential data points. We use a value of 0.5 as our cutoff for points that are influential and require additional inspection.



Appendix C: Range of Independent Variable Data Used to Construct Models

KC-135 by AMC by Quarter Model

Variable	Min	Max
1QLagAARate	0.4637	0.7091
FlyHrs/TAI	67.57	184.86

F-15E by ACC by Quarter Model

Variable	Min	Max
1QLagAARate	0.5854	0.7238
CANNhrs/TAI	23.35	101.21
1,3,5_SkillLvl/TAI	14.45	16.68

B-1 by ACC by Quarter

Variable	Min	Max
1QLagAARate	0.3797	0.6205
CANNhrs/TAI	46.94	141.59
1,3,5_SkillLvl/TAI	29.27	41.36
FlyHrs/TAI	52.89	106.99

KC-135 by AETC by Quarter

Variable	Min	Max
1QLagAARate	0.5877	0.8476
TotalEEIC644/TAI (Lag 1)	44,920	188,551
Avg Age	35.22	43.67

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13. SUPPLEMENTARY NOTES

14. ABSTRACT

In the current fiscally constrained environment, the Air Force must allocate resources where they are most needed and will be most effectively used. For aircraft, this means spending money on weapon systems in a manner that optimizes aircraft availability rates, thereby maximizing the warfighting capability of the Air Force. With that in mind, this thesis endeavors to improve the analytical capability of the Air Force by demonstrating a definitive link between operations and maintenance (O&M) spending and aircraft availability rates. In order to do that, explanatory regression models are developed that show the relationship between O&M spending and AA rates, while controlling for as many other significant variables as the data allow. Ultimately, this research was unable to show that aircraft availability rates are significantly influenced by changes in O&M spending; however, suggestions for future research and potential policy implications are discussed.

15. SUBJECT TERMS

Aircraft Availability, Centralized Asset Management, Operations and Maintenance, Regression

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